Democratic and Popular Republic of Algeria
Ministry of Higher Education and Scientific Research
University Kasdi Merbah, Ouargla
Faculty of new information and communication technologies
Department of Electronics and Telecommunications

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# A better understanding of user intention in image retrieval: Discovering the relationship between concepts, the best generalization, and the hidden concepts.

Presented by:

**Abdelmadjid Youcefa**

Supervised by:

**Mohammed Lamine Kherfi**

**Jury Members**

| | | | |
|---|---|---|---|
| Kamal Eddine AIADI | Professor | Ouargla University | President |
| Mohammed Lamine KHERFI | MCA | Ouargla University | Supervisor |
| Abdelmalek TALEB AHMED | Professor | Valencienne University | Examiner |
| Abdallah MERAOUMIA | MCA | Tebessa University | Examiner |
| Fella CHERIF | MCA | Ouargla University | Examiner |
| Djamel SAMAI | MCA | Ouargla University | Examiner |

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# DEDICATION

I dedicate this modest work to:

My beloved parents Hocine and Malika for their encouragement, affection, advice and sacrifice.

I hope you will find in this work my deep appreciation and respect for you.

My brothers and sister: Oussama, Islam, Rihab.

My grandfather: Attig Arbi and My grandmothers: Khadidja and Fatena, for your prayers and your loves.

All my family and my fiancée.

All my friends and colleagues: Bilal, Ousama, Salah, Kamel, Adel

For their precious assistant and encouragement, when I needed moral support.

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To all those who were giving me any kind of support.

Finally, I dedicate it to all those I love and appreciate.

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*A dream does not become reality through magic; it takes sweat, determination and hard work.*

# ABSTRACT

In this thesis, we study three general issues but in the specific context of the query in semantic concepts-based image retrieval: Choosing the best generalization for a set of concepts, Discovering the relationship between concepts, and Discovering hidden concepts. In the image retrieval paradigm studied, first the user formulates his query by choosing a set of images, each of which is annotated with one concept. Our goal is to understand the needs of this user by analyzing those concepts, so that the retrieval engine will be able to answer the user's needs adequately, thereby alleviating the intention gap and the semantic gap.

Understanding user needs is a very broad and extremely challenging task, this is why we focus on the three issues cited above. The first issue we deal with belongs to the family of Generalization problems which are common problems in cognitive sciences. Given a user who chooses a set of concepts with or without repetition, and given that different generalizations are possible, how to choose the best generalization among them? The second issue we study in this thesis is that of discovering the relationship between concepts. Given a raw set of concepts composing the query, we try to discover the common relationships between pairs of concepts and between bigger sets of concepts (three concepts or more), going up to common relationships between all concepts. Notice that the first and the second issue are very related to each other, since it is possible to deduct the possible and best generalizations from common relationships and vice-versa. The third issue we study is how to apply the findings of the two first issues to discover hidden concepts. Given that we have discovered the relationship between our set of concepts or generalized them to a unique concept, what are the other concepts that we can enrich the same set with? This is very useful in image retrieval since it allow to perform what is called query expansion.

To resolve the issues raised above, which are very connected, we propose two different solutions: each solution resolves the three issues simultaneously. Both solutions make use of ontologies to represent our concepts hierarchy. In addition, and rather than using one single hierarchy, we use several possible hierarchies and try to find the best one among them. Our first solution is based on Bayesian Model of Generalization (BMG). This model comes from cognitive science and has a strong mathematical background. It has been successfully applied in resolving many problems. Our second solution is based on measuring the Semantic Similarity (SS) between several concepts. We develop a new formula which permits to measure this similarity from the similarity between pairs of concepts. The experimental evaluation conducted demonstrate that the solutions we propose, and which choose the best among multiple concept hierarchies yield better results than the methods using one single hierarchy. Finally, we mention that even though our study of the raised issues (generalization from a set of concepts, discovery of relationships and that of hidden concepts) has been limited to image retrieval context, but both the study and the proposed solutions can be adapted to other applications where generalization is necessary or useful.

**Keywords:** Generalization of concepts, Image Retrieval, Bayesian models of generalization, Semantic similarity, User intention, Query expansion, Concept hierarchy.

# Résumé

Dans cette thèse, nous étudions trois problèmes généraux, mais dans le contexte spécifique de la requête en recherche d'images par concepts sémantiques : Choisir la meilleure généralisation d'un ensemble de concepts, Découvrir la relation entre les concepts et Découvrir les concepts cachés. Dans le paradigme de recherche d'images étudié, l'utilisateur formule d'abord sa requête en choisissant un ensemble d'images, chacune d'elles étant annotée avec un concept. Notre objectif est de comprendre les besoins de cet utilisateur en analysant ces concepts, afin que le moteur de recherche puisse répondre de manière adéquate aux besoins de l'utilisateur, réduisant ainsi le fossé sémantique et le fossé d'intention.

Comprendre les besoins réels de l'utilisateur est une tâche très vague et extrêmement difficile. Par conséquent, nous nous concentrons sur les trois problèmes cités ci-dessus. Le premier problème que nous allons traiter appartient à la famille des problèmes de généralisation qui sont des problèmes courants en sciences cognitives. Si un utilisateur choisit un ensemble des concepts avec ou sans répétition et si différentes généralisations sont possibles, comment choisir la meilleure généralisation parmi elles? Le deuxième problème que nous étudions dans cette thèse est celui de la découverte des relations entre les concepts. À partir d'un ensemble de concepts bruts composant la requête, nous essayons de découvrir les relations communes entre les paires de concepts et entre des ensembles plus grands de concepts (trois concepts ou plus), allant jusqu'aux relations communes entre tous les concepts. Notons que le premier et le deuxième problèmes sont très liés, car il est possible de déduire les généralisations possibles et optimales à partir des relations communes et vice-versa. Le troisième problème que nous étudions est de savoir comment appliquer les résultats des deux premiers pour découvrir les concepts cachés. Étant donné que nous avons découvert la relation entre notre ensemble de concepts ou les avons généralisés à un concept unique, quels sont les autres concepts avec lesquels nous pourrions enrichir le même ensemble? Ceci est très utile dans la recherche d'images car il permet d'effectuer ce que l'on appelle l'expansion de requêtes.

Pour résoudre les problèmes présentés ci-dessus, qui sont très liés, nous proposons deux solutions différentes: chaque solution résout les trois problèmes simultanément. Les deux solutions utilisent des ontologies pour représenter la hiérarchie de nos concepts. De plus, plutôt que d'utiliser une seule hiérarchie, nous utilisons plusieurs hiérarchies possibles et essayons de trouver la meilleure parmi elles. Notre première solution est basée sur le modèle Bayésien de généralisation (BMG). Ce modèle a été étudié en sciences cognitives et possède une base mathématique solide. Il a été appliqué avec succès à la résolution de nombreux problèmes. Notre deuxième solution est basée sur la mesure de la similarité sémantique (SS) entre plusieurs concepts. Nous développons une nouvelle formule qui permet de mesurer cette similarité à partir de la similarité entre des paires de concepts. L'évaluation expérimentale que nous avons conduite montre que les solutions que nous proposons, et qui choisissent la meilleure parmi plusieurs hiérarchies de concepts, donnent de meilleurs résultats que les méthodes utilisant une seule hiérarchie de concepts. Enfin, nous mentionnons que même si notre étude des problèmes soulevés (généralisation à partir d'un ensemble de concepts, découverte de relations et de concepts cachés) a été limitée au contexte de la recherche d'image, les études menées et les solutions proposées peuvent bien être adaptées et appliquées à d'autres applications où la généralisation est nécessaire ou utile.

**Mots clés:** Généralisation des concepts, Recherche d'images, Modèle Bayésien de généralisation, Similarité sémantique, Intention de l'utilisateur, Extension de requête, Hiérarchie des concepts.

# ملخص

في هذه الأطروحة، ندرس ثلاث مسائل عامة ولكن في السياق المحدد للاستعلام في استرجاع الصور حسب المفهوم المعنوي: اختيار التعميم الافضل لمجموعة من المفاهيم ، واكتشاف العلاقة بين المفاهيم ، واكتشاف المفاهيم المخفية. في نموذج استرجاع الصورة الذي تمت دراسته ، يقوم المستخدم أولاً بصياغة استعلامه عن طريق اختيار مجموعة من الصور ، يتم شرح كل منها بمفهوم واحد. هدفنا هو فهم احتياجات هذا المستخدم من خلال تحليل تلك المفاهيم ، بحيث يكون محرك الاسترجاع قادرًا على تلبية احتياجات المستخدم بشكل مناسب ، وبالتالي تخفيف فجوة النية والفجوة الدلالية.

إن فهم احتياجات المستخدمين مهمة واسعة للغاية وصعبة للغاية ، وهذا هو السبب في أننا نركز على القضايا الثلاث المذكورة أعلاه. القضية الأولى التي نتعامل معها تخص عائلة مشكلات التعميم والتي تعد مشكلات شائعة في العلوم المعرفية. بالنظر إلى مستخدم يختار مجموعة من المفاهيم مع التكرار أو بدونه، وبالنظر إلى أن عدة تعميمات المختلفة ممكنة، كيف يمكن اختيار التعميم الأفضل بينها؟ القضية الثانية التي ندرسها في هذه الرسالة هي اكتشاف العلاقة بين المفاهيم. بالنظر إلى مجموعة من المفاهيم الأولية التي تشكل في الاستعلام، نحاول اكتشاف العلاقات المشتركة بين أزواج المفاهيم وبين مجموعات أكبر من المفاهيم (ثلاثة مفاهيم أو أكثر)، والوصول إلى العلاقات المشتركة بين جميع المفاهيم. ونشير إلى أن المشكلين الأول والثاني مرتبطان ببعضهما البعض ، لأنه من الممكن اقتطاع التعميمات الممكنة وأفضل تعميم من العلاقات العامة والعكس صحيح. المسألة الثالثة التي ندرسها هي كيفية تطبيق نتائج المسألتين الأوليين لاكتشاف المفاهيم الخفية. بالنظر إلى أننا اكتشفنا العلاقة بين مجموعة مفاهيمنا أو قمنا بتعميمها على مفهوم واحد، ما هي المفاهيم الأخرى التي يمكننا إثراء بها هذه المفاهيم ؟ يعد هذا مفيدًا جدًا في استرجاع الصور لأنه يسمح بتنفيذ ما يسمى توسيع الاستعلام.

لحل المشكلات المثارة أعلاه، والتي ترتبط ارتباطًا كبيرًا، نقترح نهجين مختلفين: كل نهج يحل القضايا الثلاث في وقت واحد. كلا الحلين يستندان الى الأنطولوجيات لتمثيل مفاهيمنا. بالإضافة إلى ذلك ، وبدلاً من استخدام تسلسل هرمي واحد ، فإننا نستخدم العديد من التسلسلات الهرمية الممكنة ونحاول العثور على الأفضل بينها. يعتمد حلنا الأول على نموذج التعميم البايزي وقد تمت دراسة هذا النموذج في العلوم المعرفية وله أساس رياضي قوي. تم تطبيقه بنجاح في حل العديد من المشكلات. يعتمد حلنا الثاني على قياس التشابه الدلالي يبين عدة مفاهيم. نحن نقترح صيغة جديدة تسمح لنا بقياس هذا التشابه انطلاقا من التشابه بين مفهومين. توضح التجارب التي تم إجراؤها أن الحلول التي نقترحها والتي تقوم باختيار التسلسل الهرمي الافضل من بين عدة تسلسلات هرمية تحقق نتائج أفضل من الأساليب التي تستخدم تسلسل هرمي واحد. أخيرًا ، نذكر أنه على الرغم من أن دراستنا للقضايا المثارة (التعميم انطلاقا من مجموعة من المفاهيم واكتشاف العلاقات بينها واكتشاف المفاهيم الخفية) قد اقتصرت على سياق استرجاع الصور ، إلا أنه يمكن تكييف كل من الدراسة والحلول المقترحة مع التطبيقات الأخرى حيث يكون التعميم ضروري أو مفيد.



**الكلمات المفتاحية:** تعميم المفاهيم ، استرجاع الصور ، نموذج التعميم البايزي ، التشابه الدلالي ، نية المستخدم ، توسيع الاستعلام ، التسلسل الهرمي للمفهوم.

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# CHAPTER I. GENERAL INTRODUCTION

## I.1. Image retrieval

With the recent development in production and image sharing technologies, this type of media has become available in huge amounts in personal, professional, and Internet collections. This has greatly motivated the emergence of a field of research that aims to develop search engines and image indexing. The recently developed approach of image retrieval has managed to achieve some success either content-based image retrieval CBIR (Aiadi & Kherfi, 2017), (Khaldi & Kherfi, 2016)or text-based image retrieval TBIR (Clough & Sanderson, 2006),(Chen, Xu, Tsang, & Luo, 2010),(Yiming Liu, Xu, Tsang, & Luo, 2011),(Datta, Varma, & Singh, 2017),(Dinakaran, Annapurna, & Kumar, 2010),(Park, Baek, & Lee, 2003).

However, they continue to struggle to capture the semantics and to select the real needs of the user. CBIR techniques use the visual content in order to retrieve, for a given query (e.g., image example, sketch, feature vector, etc.), the similar ones. This visual content can be represented in terms of global features (Khaldi & Kherfi, 2016),(L. Wu, Hoi, Jin, Zhu, & Yu, 2009) (Ying Liu, Zhang, Lu, & Ma, 2004; Manjunath, Ohm, Vasudevan, & Yamada, 2001; Plataniotis & Venetsanopoulos, 2000; J. Wang, Li, Chan, & Wiederhold,

1999) (Y.-N. Liu, Zhang, Sang, & Wang, 2019)or local features (Lowe, 1999),(Bakar, Hitam, & Yussof, 2013),(Deselaers, Keysers, & Ney, 2004),(Mojsilovic, Gomes, & Rogowitz, 2002) (Leutenegger, Chli, & Siegwart, 2011).

TBIR technics use text (e.g., image annotation or text surrounding it) as image descriptor. Due to its simplicity and rapidity, TBIR seems to be more desirable and practical. However, the quality of TBIR depends on the quality of the annotations that are often ambiguous and incomplete. For example, the same image may be annotated with two very different annotations based on the interests or the psychological state of the annotator. Additionally the annotations may be incomplete and do not fully describe the content of the image.

In order to alleviate the limitations of query by visual example QBVE and TBIR, an alternative paradigm has been proposed and denoted as query by semantic example QBSE that combines both techniques (Rasiwasia, Moreno, & Vasconcelos, 2007),(Natsev, Haubold, Tešić, Xie, & Yan, 2007),(Rasiwasia & Vasconcelos, 2008). In current work, we are concerned with QBSE. In QBSE paradigm, the query is composed of multiple images, where each image is labeled with different keywords that describe the different visual concepts within the image (e.g., house, rain, sunset, etc.) As a query, the system uses the keywords annotating the images rather than the images themselves. In this thesis we are concerned with QBSE.

Furthermore, and in order to obtain a better performance, the system should not use concepts as they are, instead, it has to generalize them to some common or more general concepts (e.g., the user is looking for animals, landscapes, etc.). The process of moving up from a set of concepts to a more common or general concept is called "generalization" which will be our most important issue in this thesis.

## I.2. Generalization in humans

Human have the ability to identify the relationship between several visual concepts and to generalize them to higher abstraction levels. Several studies in the cognitive science and psychology (Gerken, 2004),(Gerken, 2006),(Saffran & Wilson, 2003),(Swingley, 2005) have been conducted to study generalization in humans, especially infants. The study in (Gerken, 2006) She raised the problem of what infants learn when the information presented supports multiple regularities, she indicates that infants can infer a pattern and generalize it from four different examples or types. For example consider the visual concepts in Figure I.1, and consider that there exists a hierarchy with represents all the concepts at different abstraction levels. Now, even thought there are three different concepts in Figure I.1, but human generalizes them to the concept Bird which is the common point between them all at the first abstraction level. It has also be noticed that those concepts belong also to the ancestors of *Bird*, namely *Vertebrate* in the second abstraction level and *Animal* in the third one. But despite of this, human generalizes them to the lowest common node in abstraction levels (i.e., *Bird*) rather than higher ones (i.e. *Vertebrate* or *Animal*). The basic truth of human annotations reveals that the level of generalization varies according to conceptual diversity, with greater diversity leading to wider generalization (Jia, Abbott, Austerweil, Griffiths, & Darrell, 2013). Cognitive science attempts to create models that can understand human generalization judgments and/or mimicking human generalization. Using several concept hierarchies in the process of generalization makes the system close to human judgment and could allow understanding his query in a better way. This motivated us to develop our solutions based on such hierarchical representations of humans, in an attempt to capture user intention and therefore improve retrieval performance.

**Figure I.1.Examples of visual concepts, the common concept is *Bird*.**

## I.3. Existing generalization approaches

Using queries that are composed of multiple images (i.e., multiple semantic examples) could help performing generalization, and thereby significantly improving retrieval results. However, finding the appropriate generalization for these semantic examples is a very complicated task. Recently, many studies have been done trying to understand and simulate how humans generalize. Some of those works have used machine vision techniques (Quattoni, Collins, & Darrell, 2008), others have opted for Bayesian models of generalization (Tenenbaum, 2000),(Tenenbaum & Griffiths, 2001),(Xu & Tenenbaum, 2007),(Abbott, Austerweil, & Griffiths, 2012),(Korichi, Kherfi, Batouche, & Bouanane, 2018),(Fei-Fei & Perona, 2005). Thus, a great progress has been achieved and generalization methods have been proposed. Starting from one concept hierarchy and a set of given positive concepts, the key idea is to find the appropriate level of these concepts needs to be generalized to. A concept hierarchy is made up of several abstraction levels where each level holds a set of concepts, which are represented by leaf nodes, as Figure I.2 shows.

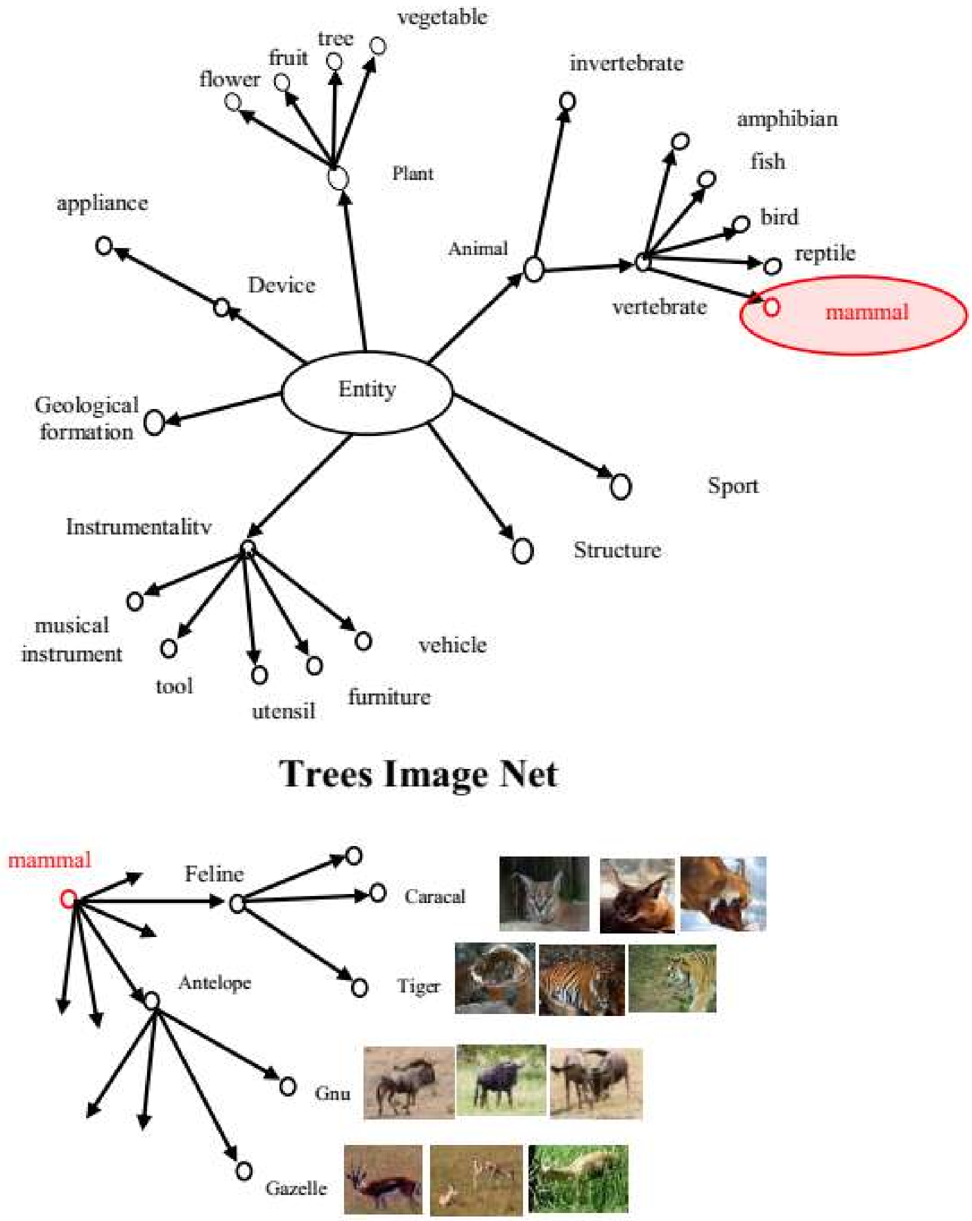



**Figure I.2. An example of a concept hierarchy and the corresponding images of some leaf nodes (ImageNet as instance).**

## I.4. Limitations of existing generalization approaches

Despite the success they achieved, existing generalization approaches suffer from a serious drawback. Indeed, first in those approaches, generalization is done using visual concept learning where a new concept is learnt from a few example images. Their main drawback comes from the fact that they use only one concept hierarchy and generalize positive example images using this hierarchy. This doesn't allow them to take into account the multitude of generalizations that are possible in many situations.

Indeed, one should know that the same set of concepts could be represented by different concept hierarchies based on the selected context. For example, animals could be categorized in a concept hierarchy based on their classes, region of leaving and diet, etc. To make things clearer, let us take the example illustrated in Figure I.3. Human can generalize the concepts Elephant, Zebra and Giraffe to one hypothesis from the following hypothesis space H= {Mammal, Africa animals, Herbivores}. A hypothesis space is a set of all the possible generalizations obtained from the concepts that compose the given query.

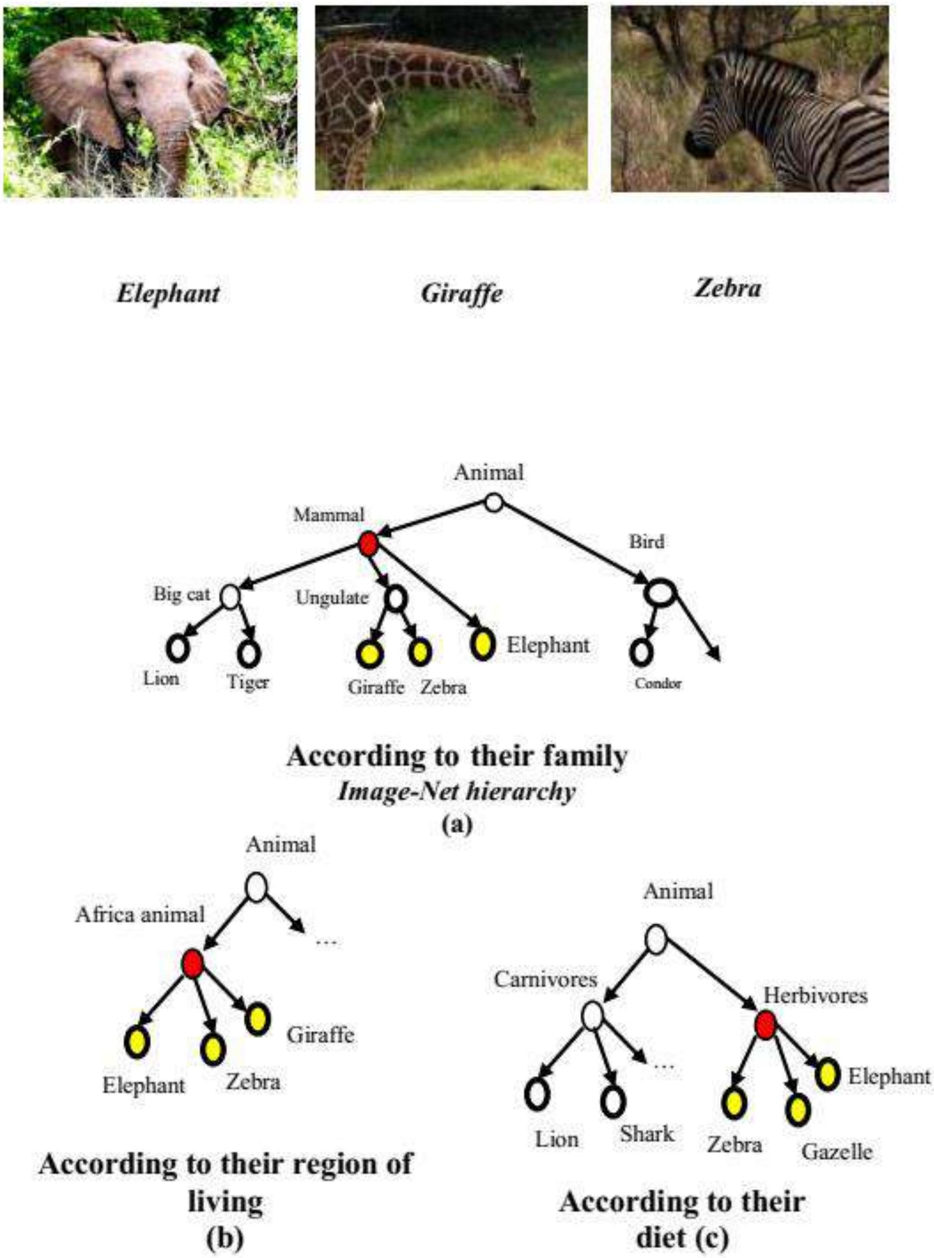



**Figure I.3. Concepts may be categorized in different ways based on the selected context, (a). Animals are categorized according to their family, (b). Animals categorized according to their living region, (c). Animals categorized according to their diet.**

As shown in Figure **I.3** (a), animals have been categorized according to their family, whereas in Figure **I.3** (b) according to their region of living and in Figure **I.3** (c) according to their diet. This means that the generalization in each case will be performed using a different concept hierarchy.

## I.5. Our research questions

In this thesis, we attempt to identify the best generalization when different generalizations are possible. To be able to solve this problem, we recourse to using a multitude of hierarchies, each created according to a given principle. In the context of animals for example, they either can be grouped according to their family, diet, place of living, etc.
Now, given a query made up of a few positive examples only, how to select the best generalization principle and also the appropriate level of abstraction. The same solution can be seen as that of discovering the common relationship between the query concepts. Finally, discovering common relationships, generalization principle and abstraction level will allow us to expand query in an attempt to discover hidden concepts.

Let us take an illustration. Suppose that the user formulates a query with the three images of Figure I.4. The retrieval system should be able to implicitly deduce the relationship between those concepts and their common points. This will allow it to enrich the query (and therefore the results) with other concepts from the same category, i.e. related to the query concepts with the same relationship identified.

**Figure I.4.Example of query formulate by user**.

In short, given a query composed of a number of concepts, the main questions we will try to answer through our work are:

- What is or are the possible relationships between those concepts?
- When concepts are represented with several hierarchies, what is the appropriate hierarchy?
- Within the chosen hierarchy, what is the appropriate abstraction level to generalize to?
- How to apply the findings (relationship or hierarchy and abstraction level) to discover hidden concepts, i.e. those intended by the user but not explicitly present in his query?
- How to improve retrieval results by adding discovered concepts to the query.

Answering these questions would partially contribute in resolving the big and very challenging task of understanding the user intention when he formulates his query:

- What user wants exactly by this query?
- What are the images that best correspond to his needs?

We recall that it is very challenging to determine what relationship assembles a set of given concepts. For example, are Lion, Giraffe and Zebra Mammals or African animals? Our approach tries to generalize the query concepts by finding the most probable/strong relationship that assembles them.

## I.6. Our contributions

In this thesis, we make many noteworthy contributions, namely:

- We study three issues in the context of semantic concepts-based image retrieval:
  - **Generalization selection**: When there are a multitude of possible generalizations of the query concepts, which is the best generalization?
  - **Discovering the relationship between the concepts**: What are the possible relationships between the concepts composing the query?
  - **Discovering hidden concepts**: Once the best generalization selected and the relationships discovered, what are the other concepts to enrich the query with, in a query expansion attempt.
- **We propose two solutions**, each of which takes simultaneously into account the three issues cited above. Both solutions make use of multiple concept hierarchies: They allow to **select the appropriate concept hierarchy** among multiple concept hierarchies.
  - The first solution is based on Bayesian Model of Generalization (BMG) model which relies on calculating prior probabilities. Our concepts are represented using a hierarchical ontology.

Then the appropriate probabilities are computed, which would allow to select the best hierarchy, i.e. that allowing to perform the best generalization.

- The second solution is based on measuring the semantic similarity between a set of concepts. Instead of pairwise metrics, which are widely considered, **we propose a new similarity metric** that allows to calculate the semantic similarity between several concepts (more than two concepts).

- Our second solution allows also to **detect the noisy concept in the query** (outliers) and therefore to discard them, which could help improving retrieval precision.
- We contribute to resolving the challenging task of grasping user intention and understanding his needs.
- By understanding the user's needs, the retrieval engine will be able to answer them adequately, thereby **alleviating the intention gap and the semantic gap**.
- Developing a new image retrieval engine that exploits the query expansion method explained above.
- **Introducing two new concept hierarchies** according to new grouping principles: diet and place of living. Those hierarchies are used for our experimental validation.

## I.7. Overview of the related work

The generalization with multiple visual concepts is a challenging task. Recent studies in cognitive science have focus to how to create a system able to mimicking human generalization when multiple stimuli have observed.

Some of works exploiting semantic hierarchy for object categories or generalization have achieved a success in recent years. Deng *et al.*(Deng et al., 2012) have suggested classifier to better recognition for objects in a hard image (i.e. image contain complex objects are difficult to identify) form a semantic hierarchy consisting of many levels of abstraction. Their aim is just to avoid making mistake in object categories, trading off specificity uncertain they give general and certain identification. However, this classifier is not completely accurate in identifying leaf node classes.

Transfer learning (Quattoni et al., 2008),(Salakhutdinov, Torralba, & Tenenbaum, 2011) proposed in computer vision, A. Quattoni *et al* (Quattoni et al., 2008), proposed a visual-category to learn a new class based on labeled examples of other related classes. The aim of this work is to minimize the number of examples necessary to learn the class, improving generalization from a few examples.

Salakhutdinov et al (Salakhutdinov et al., 2011), proposed knowledge transfer in a concept hierarchy. Their goal is improving the performance of object classification, on classes with a small number of training cases.

These two works have tried to improve the classification using only the leaves of the concept hierarchy. Thus, works did not address the issue of determining the level of abstraction within the hierarchy at which to make generalizations, which is the key idea of visual concept learning techniques.

Bayesian model of generalization (Xu & Tenenbaum, 2007), (Abbott et al., 2012), (Jia et al., 2013) proposed from cognitive science, including word learning and concept learning problem. The main idea is how to determine the degree of generalization when a set of concepts observed.

Tenenbaum *et all* (Tenenbaum & Griffiths, 2001),(Tenenbaum, 2007) proposed a method for the concept learning problem, using previous approach on models of generalization in (Shepard, 1987).

Tenenbaum and Griffiths (Tenenbaum & Griffiths, 2001) referred to this as the 'size principle' and showed how it could potentially explain a wide range of phenomena in category learning, generalization, and similarity judgment, which were not previously unified under a single rational-inference account. Tenenbaum and Xu (Xu & Tenenbaum, 2007) focus on learning names for object-kind concepts, which are typically organized into a tree-structured taxonomy with labels at various levels .Accordingly, the hypothesis space of candidate word meanings consists of all subtrees in a tree structured taxonomy of objects.

Xu and Tenenbaum (Xu & Tenenbaum, 2007) developed a Bayesian word learning model and showed their model capable to mimicking human generalization judgments to create hypothesis space for three categories (animals, vehicles, and vegetables) with few positive examples. However, their work is unable to extend their generalization to other categories.

Abbott et al (Abbott et al., 2012), propose a method for automatically generating the hypothesis space used in such Bayesian generalization frameworks. They use WordNet to generate the tree-structured hypothesis space for concepts, and ImageNet to indicate the images corresponding to these concepts. The automatically generated hypothesis space can be used in any categories, unlike previous work.

Recent work in visual recognition (Jia et al., 2013),(Verma, Mahajan, Sellamanickam, & Nair, 2012),(Yan et al., 2015),(Glick & Miller, 2016) and image retrieval (Deng, Berg, & Fei-Fei, 2011) using category hierarchical structures, they used for classification with a large number of classes using linear classifiers. (Verma et al., 2012)Proposed a new method associate separated visual similarity metrics for every concept in a hierarchy and then learn the metrics jointly through an aggregated hierarchical metric.

(Yan et al., 2015) Proposed a generic and principled hierarchical architecture, Hierarchical Deep Convolutional Neural Network (HD-CNN) that decomposes an image classification task. Deep neural networks are used in (Glick & Miller, 2016), which applies a technique similar to HD-CNN (Yan et al., 2015)to insect species classification. Deng *et al*(Deng et al., 2011), use taxonomy to learn an image similarity function for improved retrieval.

In (Jia et al., 2013), a system that integrates both Bayesian models of generalization and machine vision techniques has been proposed. Their aim is to determine whether the query image belongs to the concept generated from the set of images. The resulting combining models outperform pervious work in computer vision systems and problem of generalizing from a set of input images. They used ImageNet hierarchy to build their hypotheses space. This model is very close to human performance on this task.

In the same context, discover the relationships between concepts. Other research proposed to find the relationships between two concepts or words by measuring the similarity between them. Measuring the semantic similarity between concepts allows discovering relationships between them. Moreover, whenever the semantic similarity is highly, there are one or several relationships between them. In the literature some research (Resnik, 1995),(Lin, 1998),(Jiang & Conrath, 1997),(Z. Wu & Palmer, 1994),(Rada, Mili, Bicknell, & Blettner, 1989) attempts to find the perfect formula for calculating the semantic similarities between a pair of concepts. These researches can be classified into two categories namely corpus-based approaches and knowledge-based approaches (Mihalcea, Corley, & Strapparava, 2006). The formulas proposed previously focused on the similarity of only two concepts. But they did not propose a formula for calculating similarity between a set of concepts. In this thesis we will address this problem.

## I.8. Organization of the thesis

The rest of this thesis is organized as follows:

In **Chapter II** we present an overview on the related work to this thesis. We present the different existing methods belonging to visual concept learning, , Bayesian model of generalization, and then, we present previous methods for measuring the semantic similarity between concepts. Finally, we criticize these related works.

**Chapter III** is concerned with Bayesian Models of Generalization which are the basis of our first solution presented in Chapter V.

**Chapter IV** we will describe some notion about ontologies and concept hierarchy, which will be used to represent our concepts. We will also mention the construction of the concept hierarchy.

**Chapter V** will describe our first solution. We will explain the detail of our framework and how we use the Bayesian model to generalize with numbers of examples based in multiple concept hierarchy.

**Chapter VI** gives an experimental evaluation of our first solution. We will give results, analyze them and compare them with some sate of the art methods.

**Chapter VII** will describe our second solution which is based on calculating the semantic similarity between the query concepts.

Finally we will draw some conclusions and future works.

# CHAPTER II. LITERATURE REVIEW AND CRITICISM

## II.1. Introduction

This chapter discusses relevant state-of-the-art literature on generalization with positive examples and relevant model on semantic similarity between terms. Many literature researches in cognitive science attempt to develop a method that is able to simulate the performance of the human to learn novel visual concepts from positive examples. Previous works are focus on how a human child learns new words from a set of positive examples.

Humans are able to generalize complex sets of images that contain different objects very quickly. Besides, humans are able to extract the relationship between a given set of concepts in different contexts. By exploiting concept hierarchies, numerous attempts have been made in the literature, attempting to reach human-like object generalization or categorization.

In the remainder of this chapter, we present an overview on the related work to this thesis. At first, we start by a brief introduction to image retrieval, and then we provide details about content based image retrieval CBIR and also text-based image retrieval then ontology-based image retrieval. Moreover, We present the different existing methods belonging to visual concept learning, Bayesian model of generalization as our proposed approach is also applied for the task of generalization with positive examples. Then, we present some previous model for measuring the semantic similarity between concepts. Finally, we demonstrate the limitation of these searches.

## II.2. Related work

### II.2.1. Image retrieval

Due to the explosive growth in digital images, there has been an increasing interest in developing techniques to help users retrieving their desired images. These techniques are called "image retrieval" and they can be classified into two main categories which are, content based image retrieval CBIR (Lew, Sebe, Djeraba, & Jain, 2006),(Kherfi, Ziou, & Bernardi, 2002; L. Yang et al., 2010),(Kherfi, Ziou, & Bernardi, 2003),(Khaldi, 2017),(Aiadi, 2017)and text-based image retrieval TBIR (Chen et al., 2010),(Yiming Liu et al., 2011).

#### II.2.1.1. Text-based image retrieval

Text-based image retrieval (TBIR) techniques (Clough & Sanderson, 2006),(Chen et al., 2010),(Yiming Liu et al., 2011),(Datta et al., 2017),(Dinakaran et al., 2010),(Park et al., 2003) use keywords annotation of images to retrieve desired images from database annotated. The textual annotations are word or words given by human annotator to describe the image content. Image web search engines (i.e. Google, Yahoo!...) based on textual annotation of images in their image retrieval. When a user inputs a query using a keyword to retrieve images which he needs, TBIR techniques return relevant images which are contain the same keyword in the database. However, the retrieval performance has a significant link with the annotation of the images in the database. The text surrounding of the image can be incomplete or does not reflect exactly what the image content. This affects the performance of retrieval of images and can give insufficient results to the user. In addition, The TBIR techniques can use only in annotated database, this is represents a major drawback.

#### II.2.1.2. Content-based image retrieval

Content-based image retrieval techniques (Ashley et al., 1995),(Niblack et al., 1993) are coms to overcome the problems of the text-based image retrieval. Those techniques based on the content visual features describing the low-level content of images. CBIR consists of retrieving images using only the image itself without any other information, they only consider the digital image. Content-based image retrieval techniques were acquainted in the mid-1990s with beat the issues associated with the content based image retrieval referenced above. In the last decade, various substance based image retrieval techniques have been proposed for example techniques based on global features(Khaldi & Kherfi, 2016),(L. Wu et al., 2009)(color(Ying Liu et al., 2004; Manjunath et al., 2001; Plataniotis & Venetsanopoulos, 2000; J. Wang et al., 1999),shape(Y.-N. Liu et al., 2019),(D. Zhang & Lu, 2002),(Qi, Song, Zhang, & Liu, 2016), and texture (Manjunath et al., 2001),(Ma & Manjunath, 1999),(J. Z.

Wang, Li, & Wiederhold, 2001)) or local features (Lowe, 1999),(Bakar et al., 2013),(Deselaers et al., 2004),(Mojsilovic et al., 2002) (SIFT key points, BRISK(Leutenegger et al., 2011) ..). Query by visual example QBVE (Faloutsos et al., 1994),(Zha, Yang, Mei, Wang, & Wang, 2009),(Niblack et al., 1993),(Tolias & Jégou, 2014) is one of the most used approaches in CBIR. However, the semantic gap between the low-level visual features and the high-level semantic meaning of images causes a limitation to CBIR performance. The semantic gap could be defined as the contradiction between the human judgment and CBIR results. In other words, the semantic gap is the discrepancy between two interpretations, one of the user and the other of the machine (Aiadi & Kherfi, 2017).

#### II.2.1.3. Ontology-based image retrieval

Ontology-based image retrieval (Filali, Zghal, & Martinet, 2016),(Deepa, 2017) utilizes knowledge representations which join the features of text based image retrieval and content-based image retrieval. Ontology gives the best approach to sort out the web data in organized manner. Content-based retrieval is a proficient strategy that considers low-level features of image information, the role of using some textual keywords to describe the content of an image to support the retrieval system. The primary reason on ontology is to represent the image in semantic way. Ontologies based images retrieval approaches have been proposed to extricate visual data guided by its semantic content.

## II.2.2. Query Formulation in image retrieval

The formulation of the query is a phase of communication between the user and the search system (Kherfi, 2008). The user can expresses his/her needs using text query by text or image query by image example.

### II.2.2.1. Query by text QBT

**QBT**, which used in text-based image retrieval. User formulates his/her query by using a text (keywords) expresses his/her needs. Each image in database should annotate with keyword which explain the content of the image. The system TBIR search images annotated with the same keywords in the query, as shown in Figure II.1 the results of the word "horse "in Google image.

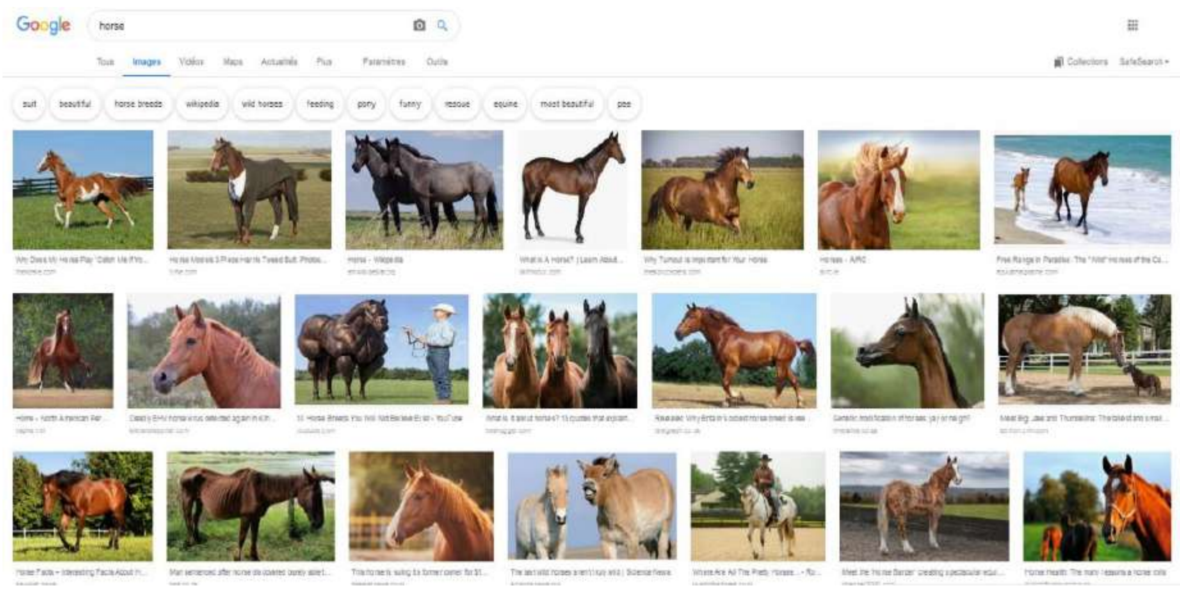



**Figure II.1. The results of the Google image search for the word "horse".**

### II.2.2.2. Query by visual example QBVE

QBVE is one of the most used approaches in CBIR. User formulates his/her query by image example represent his/her needs. This technique use the visual content of image (color, shape, and texture) to retrieve images which similar the image example in the query. Figure II.2 shows the results of the Google image search for the image of "tiger".

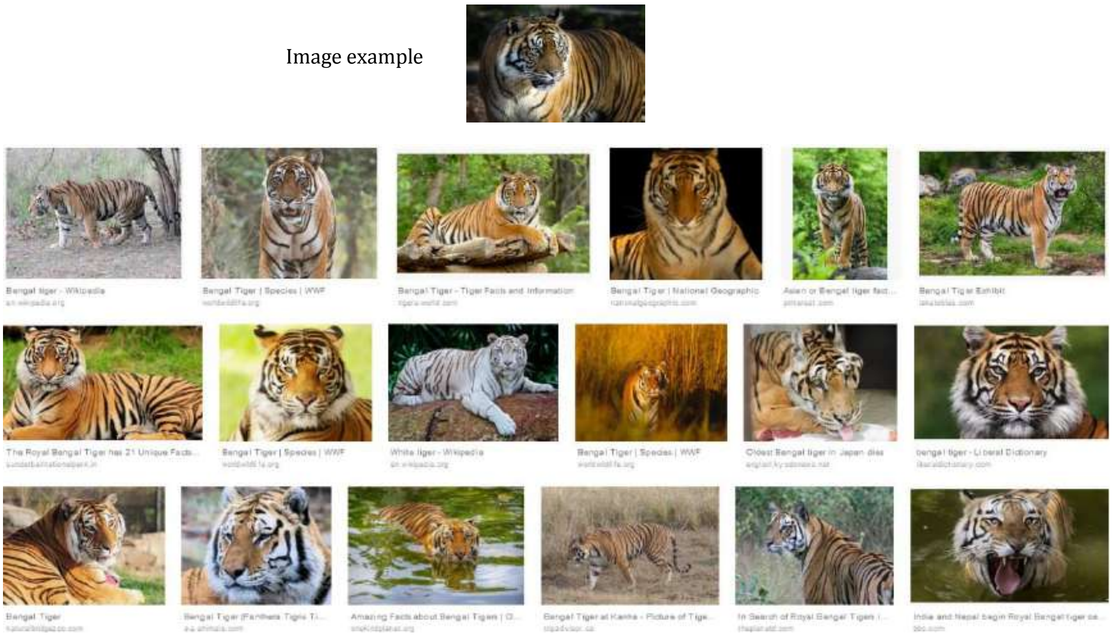



**Figure II.2 . The results of the Google image search for the image of "tiger".**

#### II.2.2.3. Query by semantic example QBSE (Rasiwasia et al., 2007)

This technique is the combination of the tow techniques above. The query contains image example but the search is done on the level of the semantic (keyword of image) as demonstrate in Figure II.3. Here, the collocation of images should be annotated. The query can also contain more than image example, it can be multiple image examples. The focus of this thesis lies in the techniques of analyzing queries composed of multiple semantic examples (multiple images).

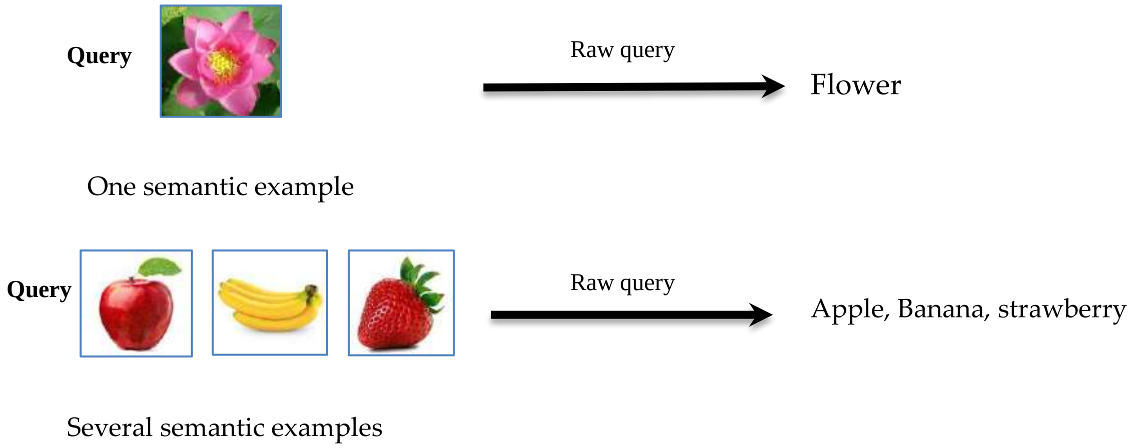



**Figure II.3. Query by semantic example QBSE, it can be more than one example.**

## II.2.3. Bayesian Model of Generalization BMG

Bayesian models of generalization (Tenenbaum, 2000),(Tenenbaum & Griffiths, 2001),(Xu & Tenenbaum, 2007) have been extensively used in cognitive science in order to resolve the issue of learning new words or concepts from an initial set of words or concepts. Given a concept hierarchy, Bayesian models of generalization basic idea revolves around finding the optimal degree of generalization, in this hierarchy, for any set of concepts. Tenenbaum and Griffiths, (Tenenbaum & Griffiths, 2001) have referred to such an approach as '*the size principle*' and they have shown how it could potentially explain a wide range of phenomena in category learning, generalization, and similarity judgment. Such phenomena were not previously unified under one single rational-inference. In more recent work, the authors in (Carey, 1978) have tried to explain how a human child learns new words from a set of pre-provided positive examples. Xu and Tenenbaum (Xu & Tenenbaum, 2007) have developed a new Bayesian word-learning model. Their model appeared to be capable of mimicking human generalization judgments to create a hypothesis space for three categories (animals, vehicles, and vegetables) with few positive examples. However, their work is too hard to be extended to other categories.

Abbott et al, (Abbott et al., 2012) have proposed a Bayesian-based model for automatically generating hypothesis spaces that are used for generalization. In their model, WordNet database has been used to generate the tree-structured hypothesis space for different concepts. WordNet is a database that encodes the semantic relationships between concepts as a network. On the other hand, ImageNet has been used to indicate the images corresponding to each of these concepts. Unlike the previous works, Abbott's automatically generated hypothesis space that can be used in any category.

Jia et al. (Jia et al., 2013) have proposed a system that integrates both Bayesian models of generalization and machine vision techniques. Their main aim was to determine whether a query image is related to a concept generated from some given set of images. Likewise, they have used ImageNet database to build their hypothesis space. In addition to the high performance their system shows, it seems to be similar to human reasoning in generalization.

### II.2.4. Semantic Similarity (SS)

Semantic Similarity is a form of measurement that quantitatively identifies the relationship between two words or concepts based on the similarity or closeness of their meaning. In the recent years, there have been noteworthy efforts to compute SS between pairs of concepts by exploiting various knowledge resources such as linguistically structured (e.g. WordNet) and collaboratively developed knowledge bases (e.g. Wikipedia). Like the Bayesian models of generalization, the challenge of computing semantic similarity SS between concepts is to propose a model that can simulate the thinking process of human. Several methods for determining semantic similarity between concepts (terms) (Resnik, 1995),(Lin, 1998),(H. Liu, 2012), (Debbagh, Kherfi, & Babahenini, 2017) have been proposed in literature and most of them (Popescu, Moëllic, & Millet, 2007),(Ambika & Samath, 2012),(S.-B. Zhang & Lai, 2015),(Taieb, Aouicha, & Hamadou, 2014) have been tested on ontology such as the WordNet "is-a" taxonomy, and others,(Debbagh et al., 2017),(Medina, Fred, Rodrigues, & Filipe, 2012),(Chen et al., 2010) used Wikipedia to compute the semantic similarity between concepts. The semantic similarity exploited many domains namely, Information retrieval, Intelligent artificial, and natural language processing, knowledge management.

The proposed methods of measuring semantic similarity focus on computing the SS between two concepts Sim $(C_1,C_2)$. However, they did not address the measurement of similarity between a set of concepts Sim(C1,C2…Cn). In our research we propose a new metric for computing the semantic similarity between a set of concepts based on the previous formulas. Besides, the previous measurements of similarity are mainly based on the ontology, they used only one type of ontology. In our work, instead of using one single ontology, we adopt three types of ontology (concept hierarchy) as demonstrated in Figure II.6 . This is for the purpose of finding relationships between the concepts of the query and discovering the appropriate concept hierarchy for generalizing them and also finding the hidden concepts. This proposal represents the second solution in our research. We will provide the details of this solution in chapter VII.

## II.3. Limitation of the related work

Despite the successes achieved by previous works in the field of generalization, they suffer from one major problem since they perform generalization using only one concept hierarchy. Therefore, they are restricted to only one context of generalization unlike humans. This problem is the first issue in our research. (**Discovering the appropriate generalization for a set of concept hierarchies)**

To make this latter point clearer let's take the example illustrated in Figure **II.4**. In Figure **II.4** (a), the relationship between the three images comes in terms of Family (i.e., Birds), whereas in Figure **II.4** (b) another kind of relationship gathers the three images, which is living region (i.e., Asia Animals). Finally, in Figure **II.4** (c), the relationship is the diet (i.e., omnivores).

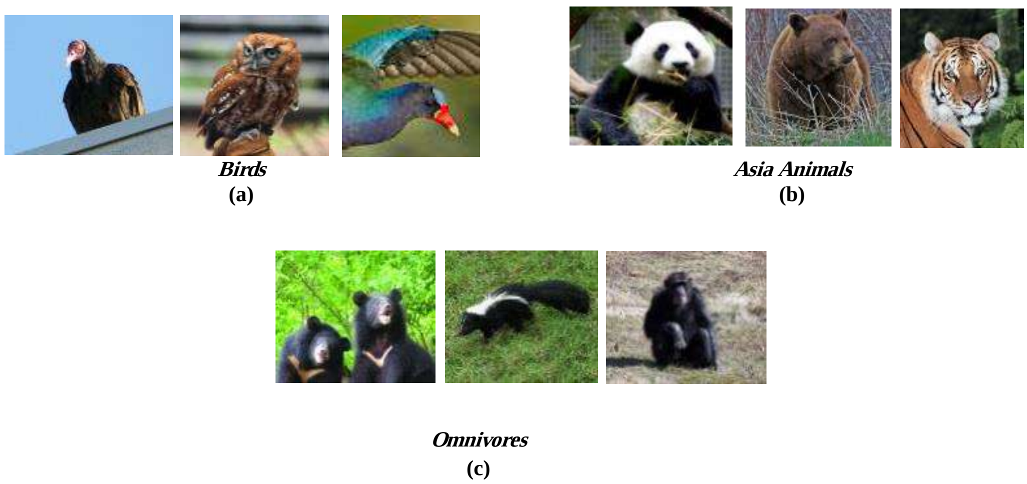



**Figure II.4. Examples of some generalizations in different contexts. (a). generalization by family, (b).generalization by living region, (c) generalization by diet.**

Supposing that we have a query that contains three concepts: Elephant, Zebra, and Giraffe as we have shown previously in Figure I.2. Conventional systems (Jia et al., 2013) interpret, or rather generalize, this query to the concept Mammal, which is totally correct. However, several other meaningful concepts can be inferred. These concepts, such as African animal, may be closest to the user intention than the concept Mammal. In order to remove this confusion and precisely detects the user intention, we propose to enrich the existing hierarchies with other ones; for example, adding the hierarchy that assembles concepts according to their region of living and also according to their diet. Figure II.5 shows the difference between our generalization and that of a conventional system.

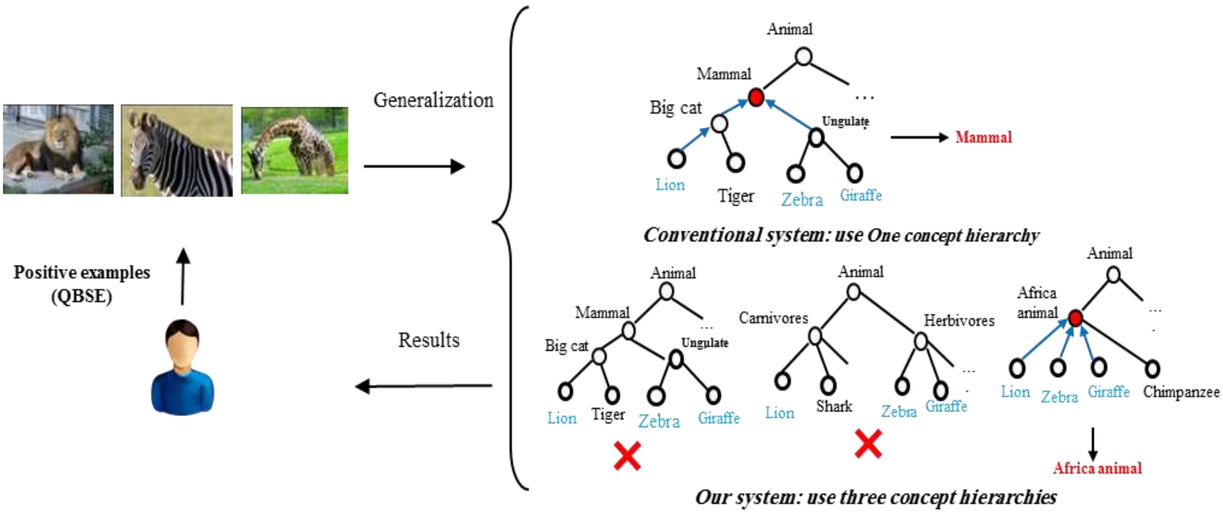



**Figure II.5. Illustrates the difference between our generalization scheme and a conventional system.**

We create new concept hierarchies to generalize the concepts in the query. Each concept hierarchies CH have multiple levels as shown in Figure **II.6**. Our goal is to find the best parent node of concepts in the appropriate CH which represents the relationship between them. Then we extract the hidden concepts which linked by the relationship selected. Finely show the results which contain images labeled by all concepts of this relationship. To investigate this formwork, we use Bayesian model of generalization, first we compute the posterior probability of all hypotheses in each concept hierarchy. Then we choose the max posterior probability of generalization and select the appropriate level, thus allowing a better understanding of the user intention.

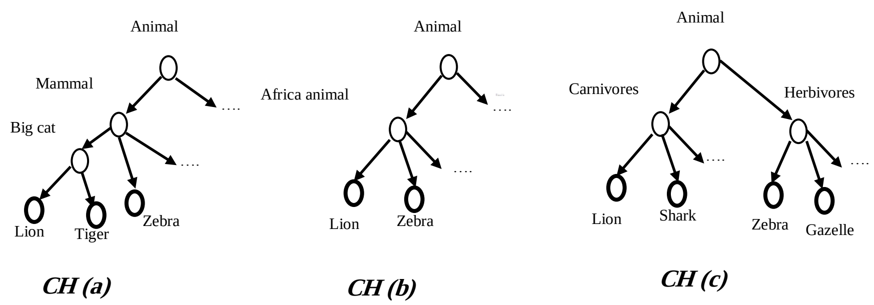



**Figure II.6. The different concept hierarchies (CH) that can be used with animals.(a) Class-based concept hierarchy, (b) region-based concept hierarchy and (c) diet-based concept hierarchy.**

As we mentioned before previous work use one concept hierarchy CH in the process of finding the appropriate level abstraction between concepts. The main issue is starting from only one type of hierarchy a how to determine the degree of generalization when a set of concepts observed. It means that the relationships extracted, are limited to only one field and does not take into account other type of relations in the other fields. That is, it cancels some relations and focuses on one type of relationship. This is another drawback for using only one concept hierarchy. This problem is the second issue in our research. (**Discovering the relationship between)**

Some works using Bayesian model of generalization, they focused on solving the following issue:

Given a set a set of observed concepts are members of an unknown concept C. they are studied whether another new concept $y$ belongs to this group or not. In order to solve this problem, they first generalize the first set of observed concepts and found the concept C that would bring them together, and then they compute the probability that the new concepts $y$ is also belongs to the same concept C using Bayesian model of generalization. Hence, we note that they did not care about finding all the hidden concepts that belong to the same concept. Here we note that they did not care about finding all hidden concepts that belong to the same concept but focused on studying the belonging of one hidden concept to the group. This is the third issue that will be studied in our research. (**Discovering hidden concepts**)

In Chapter V, we introduce the details of our first solution based on Bayesian model of generalization where we try to improve the generalization task by making it able to deal with multiple concept hierarchies.

## II.4. Conclusion

In this chapter, we have focused our attention on the previous work in visual concept learning, generalization with example positive and the semantic similarity. We have presented the different existing approaches, namely, Bayesian model of generalization, Semantic similarity. We have given details about each of these approaches. In addition, we have put the light in the limitation of those approaches and how our proposed approach deals with those limitations.

# CHAPTER III. BAYESIAN CONCEPT LEARNING

## III.1. Introduction

The ability to learn concepts from examples is one of the core capacities of human cognition. Human concept learning is remarkable for the fact that very successful generalizations are often produced after experience with only a small number of positive examples of a concept. Machine concept learning attempts to close the gap between Human concept learning and machine concept learning by developing a rigorous theory for concept learning from limited positive evidence and testing it against real behavioral data. The Bayesian Concept Learning has been successful in explaining how human generalize a property from a few observed stimuli to novel stimuli, across several different domains. They have been remarkably successful at explaining human generalization behavior in a wide range of domains.

In this chapter, we present the Bayesian model of generalization. At first, we start by explain what is the generalization then we will demonstrate the Bayesian Concept Learning model as our proposed approach is also applied. Finally, we define the Hypothesis space and we will explain the size principle.

## III.2. Generalization

Generalizations are one of the most common forms of reasoning. Generalization is to take a simple example of something that becomes the rule. Generalization is the Inference to the own situation on the general situation. Generalizing involves attempts to identify general patterns, gauge what is typical or average, or formulate general rules. Generalizing is necessary, indispensable. Imagine what life would be like if you couldn't form generalizations-if all knowledge was particularized and fragmented.

Why generalization?

- To facilitate the process of classifying things
- To facilitate the issuance of judgment.

There are incentives to make the human being generalize, if the human being finds similarities between the cases then he is generalized, we use generalizing from examples rather than to describe precisely the psychological processes involved.

### III.2.1. Inductive and deductive generalizations

Two types of generalizations: inductive and deductive

#### III.2.1.1. Inductive Generalization

Inductive generalization is an inference that goes from the characteristics of some observed sample of individuals to a conclusion about the distribution of those characteristics in some larger population (Josephson, 2000).

#### III.2.1.2. Deductive Generalization

The proceeds from a general rule or general principle to a specific case example: Brazilians love soccer. Hector is from Brazil, so he probably loves soccer too.

## III.3. BAYESIAN CONCEPT LEARNING

Bayesian system for concept learning and generalization methods (Tenenbaum, 1999),(Tenenbaum, 2000),(Tenenbaum & Griffiths, 2001),(Xu & Tenenbaum, 2007) are especially helpful for the situation where learning is performed utilizing just few positive examples. Specifically, the issue can be looked to as follows:

Given a set of $n$ examples $X=\{x_1\ldots.x_n\}$ which can be grouped under a specific concept $C$. Given a new example $y$, the question is: Is y a member of $X$ or not. To answer this question, Bayesian concept learning assumes the existence of a hypothesis space $H$ such that $H=\{h_1\ldots.h_n\}$ where the most appropriate hypothesis $h_i$ can be considered as $C$. Each hypothesis $h_i$ corresponds to one cluster in the concept hierarchies.

### III.3.1. The posterior probability

The Bayesian learner evaluates these hypotheses by computing their posterior probability $P(h|X)$ proportional to a product of prior probability $P(h)$ and likelihood probability $P(X|h)$ The Bayesian learner evaluates all the hypotheses $hi$ using Bayes rule as follows:

$$P(h \mid X) \propto P(h) P(X \mid h) \qquad (1)$$

Such that *P(h|X) is* the posterior probability, *P(h)* the prior probability and *P(X|h)* the likelihood.

## III.3.2. The prior probability

The degree of belief assigned to some hypothesis h before having seen the data, denoted *P(h)*. The prior *P*(*h*) of the hypothesis was defining to be Erlang distribution as follows:

$$P(h) \ \alpha \ \left(|h| / \sigma^2\right) \exp \left\{-|h| / \sigma\right\} \qquad (2)$$

Where $|h|$ is the size of the hypothesis *h* (number of leaf nodes) and σ parameter is a value of favors medium sized hypotheses of basic level.

## III.3.3. The likelihood

The likelihood follows is typical defines from assuming strong sampling where objects are generated uniformly at random from the true hypothesis:

$$p(X \mid h) = \left[\frac{1}{|h|}\right]^n \text{ if } x_1, \ldots, x_n \in h \qquad (3)$$

$$= 0 \text{ if any } x_i \notin h$$

The likelihood is determined by the assumption of randomly sampled positive examples.

Prior work focused on calculating the probability that a new object $\boldsymbol{y}$ is also a member of the concept $\boldsymbol{C}$ by averaging the predictions of all hypotheses weighted by their posterior probabilities:

$$P(y \in C \mid \mathrm{X}) = \sum_{h \in H} P\left(y \in C \mid h\right) P\left(h \mid \mathrm{X}\right) \tag{4}$$

In the proposed approach, however, we focus on finding the hypothesis $h$ that corresponds to the concept $C$. In particular, we haven't a new example $y$, but rather a query $X$.

To determine the most appropriate $h$ from $H$, we calculate the posterior probability for each $h$, the appropriate $h$ that corresponds to the concept $C$ is the one having obtained the highest probability score (i.e., Maximum a Posteriori hypothesis $h_{MAP}$). The $h_{MAP}$ is given by

$$h_{MAP} = \underset{h \in H}{\mathrm{argmax}}\, P(X \mid h) P(h) \tag{5}$$

## III.4. The hypothesis space

Hypothesis space: The set of all hypotheses a learner could entertain. This is divided into the latent hypothesis space, which consists of all logically possible hypothesis spaces and is defined by the structure of the learning problem, and the explicit hypothesis space, which contains the hypotheses a learner has explicitly considered or enumerated.

## III.5. Size principle

The issue of generalization in this setting is to construe, given a set of positive (+) and negative (-) instances of a concept, which different focuses have a place inside the rectangle represented in Figure III.3.(a). We consider the question most pertinent for psychological displaying: how to generalize from only a few of positive precedents?

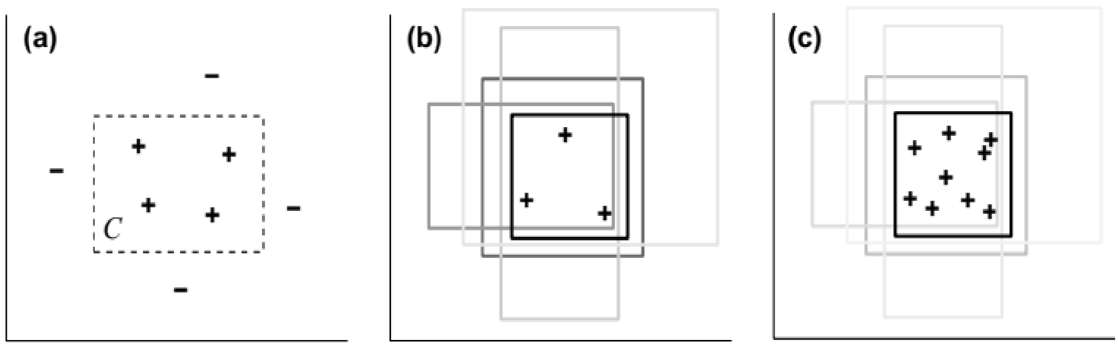



**Figure III.1. The size principle in Bayesian concept learning(Tenenbaum, 1999).**

The **size principle**: smaller hypotheses become more likely than larger hypotheses Figure III.1.(b) darker rectangles are more likely, and they become exponentially more likely as the number of consistent examples increases Figure III.1. (c). The size principle is the key to understanding how we can learn concepts from only a few positive examples.

## III.6. Conclusion

In this chapter, we have presented fundamental notions related to Bayesian concept learning. In particular, we have demonstrated the strong need for generalization. Then, we have explained the principle Bayesian model of Generalization. In addition, we have explained the constructing a Hypothesis Space and size principal. In the next chapter we will talk about ontologies and how we will use it in our approach.

# CHAPTER IV. ONTOLOGY

## IV.1. Introduction

To represent and exploit the data and information of a domain, we have to organize those data. This process allows facilitating Information retrieval and utilizing these data. The ontologies come to take care of these issues. Ontologies are used to capture knowledge about some domain of interest. An ontology describes the concepts in the domain and also the relationships that hold between those concepts. Ontology is used in many filed, especially in artificial intelligence; Information retrieval, Image retrieval, Automatic image annotation, Semantic similarity …etc.

The aim of this chapter is to provide the basics to understand the notion of ontology. At first we will give the definition of the ontology, then the components of the ontology. In addition, we mention the types of ontology, and also languages ontology. Finally, we will give the definition and the construction of the concept hierarchy witch used in our approach.

## IV.2. Ontology

Since the start of the 1990s ontology has turned into a popular research point investigated by several artificial intelligent research networks including knowledge building, natural language handling, and knowledge representation. The ontology is belongs to the field of philosophy that is concerned with the study of being or existence. Word "ontology" comes from the Greek words "ontos" means (study of being) and "logos" means (word). Ontology consists primarily of concepts and the relationships between them. A highly cited definition is (Gruber (Gruber, 1993)):

"An ontology is a formal, explicit specification of a shared conceptualization. 'Conceptualization' refers to an abstract model of phenomena in the world by having identified the relevant concepts of those phenomena. 'Explicit' means that the type of concepts used, and the constraints on their use are explicitly defined. 'Formal' refers to the fact that the ontology should be machine readable. 'Shared' reflects that ontology should capture consensual knowledge accepted by the communities".

A conceptualization is an abstract, simplified view of the world that we want to represent. Ontologies have become an indispensable means to represent and exploit data and knowledge of a domain.

Borst (Borst & Borst, 1997)and Gómez-Pérez (Gómez-Pérez, 1999), they have modified the previous definition of Gruber (Gruber, 1993):

"Ontology is defined as a formal specification of a common conceptualisation".

An Ontology is a graph the data structure. Every node of this graph stands for a "concept." A concept is a unit that one can think about. Concepts correspond to words or short phrases. Typically, concepts correspond to nouns or noun phrases, but they don't have to. Examples: house, man, car, New York, World Trade Center

The nodes of the ontology are connected by different kinds of links. The most important kind of link is called IS-A link. The nodes and IS-A links together form a Rooted Directed Acyclic Graph (Rooted DAG). Rooted means that there is one single "highest node" called the Root. All other nodes are connected by one IS-A link or a chain of several IS-A links to the Root. For examples; A car IS-A vehicle, A dog IS-A animal.

Why would someone want to develop an ontology? Some of the reasons are(Noy & McGuinness, 2001):

- To share common understanding of the structure of information among people or software agents
- To enable reuse of domain knowledge
- To make domain assumptions explicit
- To separate domain knowledge from the operational knowledge
- To analyze domain knowledge

## IV.3. Components of ontology

In this section, we present the main components of ontology namely, concepts, relations, axioms and instances (Stevens, Goble, & Bechhofer, 2000):

### IV.3.1. Concepts

A concept represents a set or class of entities or 'things' within a domain. Concepts fall into two kinds:

- Primitive (canonic) concepts are those which only have necessary conditions (in terms of their properties) for membership of the class
- Defined (non-canonical) concepts are those whose description is both necessary and sufficient for a thing to be a member of the class.

### IV.3.2. Relations

Relations are links between pairs of concepts. Relationships between concepts in ontology determine how term is related to different term. Typically a relation is of a particular sort (or class) that determines in what sense the concept is related to the next concept in the ontology. Relations also fall into two broad kinds: Taxonomies and Associative relationships.

- Taxonomies organize concepts into sub-super concept tree structures. The most common forms of these relations are: Specialization relationships commonly known as the 'is a kind of' relationship, and Portative relationships which describe concepts that are part of other concepts.
- Associative relationships are used to make links between concepts across tree structures.

### IV.3.3. Axioms

Axioms are used to constrain values of classes or instances. In this sense, the properties of relations are kinds of axioms. Axioms, however, include more general rules. Their inclusion in ontology may have several aims: define the meaning of the components; define restrictions on the value of attributes; set restrictions on the arguments of a relation; check the validity of specific information; infer new information.

### IV.3.4. Instances

Instances are the things represented by a concept. They represent the extensional definition of ontology.

## IV.4. Ontology Types and Frameworks

(Styrman, 2005) classified the ontologies into different types according on their generality levels. Any information structure can be called 'an ontology': For instance the table of contents in a text book, a front cover of a text book and a data base can all be considered as ontologies. There is not a widely accepted classification of ontology types, but some ontology types can be distinguished among others:

### IV.4.1. Representational ontologies

Without sticking to any particular domain this kind of ontology provides representational primitives. Exact purposes of the primitives are not expressed by this ontology, but they provide a framework that enables the usage of the provided representational primitives. Examples of the representational ontologies are the Class structure and Resource structure Description Framework Schema (RDFS). Class structure is same as file and folder organization on computer system.

### IV.4.2. Top level, generic, core, and common-sense ontologies:

Capture the common-sense human knowledge about everyday life providing basic notions about concepts like space, state, event, etc. Thus they are valid across several domains and provide a basic, domain independent vocabulary and object specifications to be used as the basis of other, more domain specific ontologies.

### IV.4.3. Metadata ontologies:

For describing the contents of on-line information resources in the web a vocabulary or category has been provided.

### IV.4.4. Domain ontologies:

Describe a reusable vocabulary of a given domain of interest. These ontologies may be used as the foundation of domain specific ontology. Domains happening around such as promotions etc. are described by this kind of ontology.

## IV.5. Ontology Languages

In computer science and artificial intelligence, Ontology languages are formal languages used to construct ontologies. They allow the encoding of knowledge about specific domains and often include reasoning rules, which support the processing of that knowledge to draw some intelligent information. Some of the languages are:

### IV.5.1. RDF (Resource Description Framework)

Developed by the World Wide Web Consortium (W3C) to describe Web resources, is a model of graphs for describing meta data by enabling automated processing (Lassila & Swick, 1999). The RDF data model is equivalent to semantic network formalism. It consists of three types of objects: *the resources* are described by RDF expressions and are always identified by URIs (Uniform Resource Identifiers); *properties* define specific aspects, characteristics, attributes or relationships used to describe a resource; and finally statements assign a value to a property of a specific resource (this value can be another RDF element).

### IV.5.2. RDFS (Resource Description Framework Schema)

**RDFS** is an extensible knowledge representation language, providing basic elements for the description of ontologies, intended to structure RDF resources. This is most simple language among all the XML based language(McBride, 2004).

### IV.5.3. OIL (Ontology Interchange Language)

OIL enables semantic interoperability between Web resources. Its syntax and semantics are based on existing propositions (OKBC, XOL and RDF (S)), providing modeling primitives like those used in frame-based approaches and ontological engineering (concepts, concept taxonomies , relations, etc.), formal semantics and reasoning procedures inspired by LD approaches. OIL have the following layers: the core OIL (OIL), which groups OIL primitives that have direct correspondence with RDF (S) primitives; Standard OIL (OIL Standard) is the complete OIL model that uses a larger number of primitives than those defined in RDF (S); OIL instances (OIL instances) add instances of concepts and roles to the previous model; and OIL "heavy" (heavy OIL) is the layer that contains the future extensions of OIL.

### IV.5.4.DAML (DARPA Agent Markup Language)

**DAML** aims to enable the next generation of the web, which actually understands the meaning of contents. It is a semantic markup language for web resources. It builds on earlier W3C standards such as RDF and RDF Schema, and extends these languages with richer modeling primitives. Current research in DAMN is leading toward the expression of ontologies and rules for reasoning and action. Much of the work in DAML is now incorporated into OWL.

### IV.5.5. DAML + OIL (DARPA Agent Markup Language + OIL)

Was developed by a joint effort between the US and EUROPE (IST) as part of DAML, a DARPA project that aims to enable semantic interoperability in XML(Fensel, Van Harmelen, Horrocks, McGuinness, & Patel-Schneider, 2001). Therefore, DAML + OIL share the same goal as OIL. DAML + OIL are built on the basis of RDF (S) and OIL. He has more reasoning abilities. OIL Ed, Onto Edit, Protégé, and Web ODE are tools for editing ontologies in DAML + OIL.

### IV.5.6. OWL (Web Ontology Language)

**OWL** is designed for use by applications that need to process the content of information instead of just presenting information. It facilitates greater machine interoperability of information by providing additional vocabulary along with formal semantics. OWL is based on earlier languages OIL and DAMN+OIL, and is now a W3C recommendation. OWL is a major technology for the future implementation of semantic web. It is playing an important role in an increasing number of applications, and is the focus of research into tools, reasoning techniques, formal foundations and language extensions.

### IV.5.7. SWRL (Semantic Web Rule Language)

**SWRL** is a proposal for semantic web rules language, combining sublanguages of the OWL Web Ontology Language (OWL D Land Lite) with those of the Rule Markup Language. Rules are of the form of an implication between an antecedent and consequent. The intended meaning can be read as: whenever the conditions specified in the antecedent hold, then the conditions specified in consequent must also hold.

## IV.6. Concept hierarchy

Concept hierarchy is one of the most popular backbones of ontology which organizes the concepts according to hyponymy relationships, and stores massive entities as the instances of the concepts. (Karthikeyan & Karthikeyani, 2015) propose a concept hierarchy extraction of web data according to ontology. The technique used in the system is named a Markov Logic Network. After experiment result concludes that this technique could provide concept hierarchy extraction with higher efficiency . An open concept hierarchy, e.g. WorldNet and ImageNet.

A concept hierarchy consists of concepts and relationships between them (H. Yang, 2011). To develop a concept hierarchy, the initial step is to decide the concepts. Concept extraction is the way toward distinguishing concepts from an arbitrary record accumulation. Concept hierarchies are in fact important because they allow to structure information into categories.

A concept hierarchy defines a sequence of mappings from a set of low-level concepts to higher-level, more general concepts. Consider a concept hierarchy for the Mammal. Each animal, however, can be mapped to the class to which it belongs. For example, Fox can be mapped to canine, and lion to big cat. These mappings form a concept hierarchy for the dimension *class*, mapping a set of low-level concepts (i.e., lion, giraffe, zebra, fox…) to higher-level, more general concepts (i.e., Mammal). This concept hierarchy is illustrated in Figure IV.1.

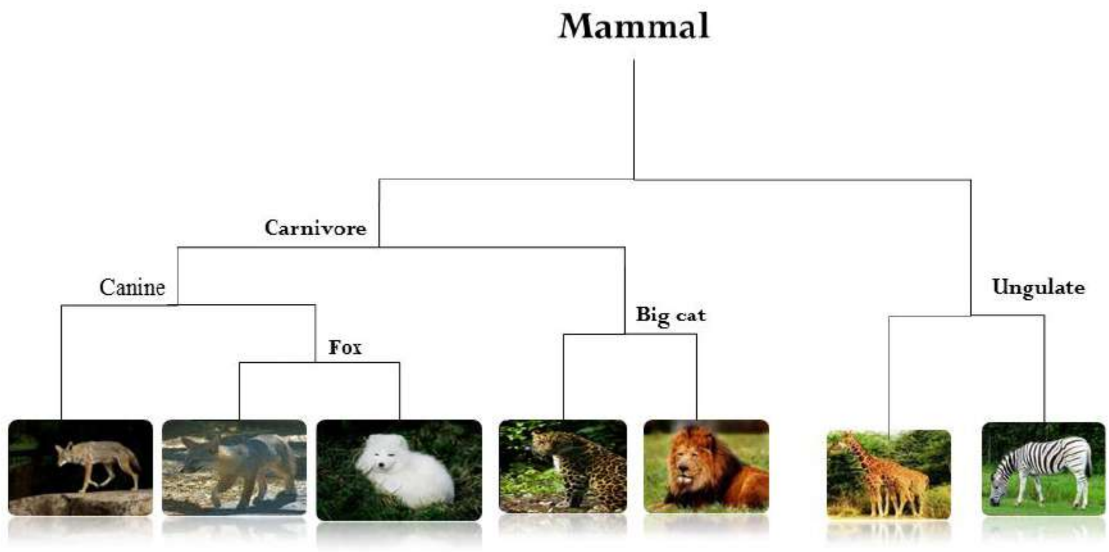



**Figure IV.1. A concept hierarchy for Mammal.**

Concept hierarchy construction concerns task specifications and user preferences. With a large set of unstructured data, the goal of Concept hierarchy construction is to organize the relevant information within a domain into an easy to understand concept hierarchy that suits specific needs for both the user and the task. Concept hierarchy construction consists of two subtasks: concept extraction and relation formation.

## IV.7. Conclusion

In this chapter we have presented some notions related to ontology. We have also explained the concept hierarchy, and how to construct a concept hierarchy. Where, we will add concept hierarchies in our work, which we will mention it in detail in Chapter V.

# CHAPTER V. OUR FIRST CONTRIBUTION: USING BAYESIAN MODEL OF GENERALIZATION

## V.1. Introduction

Previous studies have attempted to learn new concepts using a few numbers of positive examples. However, these studies have used a poor generalization. They have focused only on choosing the appropriate generalization level in a single concept hierarchy. We use the Bayesian model of generalization to generalize the concepts observed in the query. In addition, instead of using one concept hierarchy, we use multiple concept hierarchies. Generalization in several concept hierarchies allows us to know all the possible relationships between these concepts without eliminating any kind of relationships. These relationships are called hypotheses space. Then, Bayesian model of generalization computes the posterior probability of each hypothesis. The best generalization is the relationship that has the max a posterior probability. Moreover, based on the appropriate relationship selected, we study the possibility of other hidden concepts and extract them.

In this chapter, we will present the effectiveness of the Bayesian model of generalization model by using it in image al retrieval .In the image retrieval paradigm studied, first the user formulates his query by choosing a set of images, each of which is annotated with a concept. Hence, we generalize the concepts query as we mentioned above. We will explain the steps of the method we propose, and show how it overcomes the raised issue.

In the remained of the chapter, we start by giving details about our generalization scheme, after that we define the steps of our algorithm and formal details then we present the concept hierarchies CHs used in our generalization. Finally we present the analysis queries in our approach.

## V.2. Our generalization scheme

Despite the efforts of the research initiatives listed in the previous chapter, Bayesian generalization is used in the literature (Xu & Tenenbaum, 2007), (Abbott et al., 2012), (Jia et al., 2013) to generalize with few positive examples. It's based on finding the appropriate level from one concept hierarchy. They use one concept hierarchy in the process of generalization. Most improvements have been achieved by Bayesian generalization. However this generalization it's insufficient. For example, if the positive examples are: Algeria and Emirates, we can choose the concept Arab world, and if the selected concepts are: Algeria and Mali, we can choose the concept Africa. Here we have two concepts hierarchies possible, the first is according the language and the second is according the location. That is why we have added a multiple concept hierarchy.

In our approach we use Bayesian generalization to generalize in multiple concept hierarchies. This generalization gives better results than the conventional generalization. Our generalization allows improving the understanding of user intention. The details of our generalization scheme are illustrated in Figure V.1.

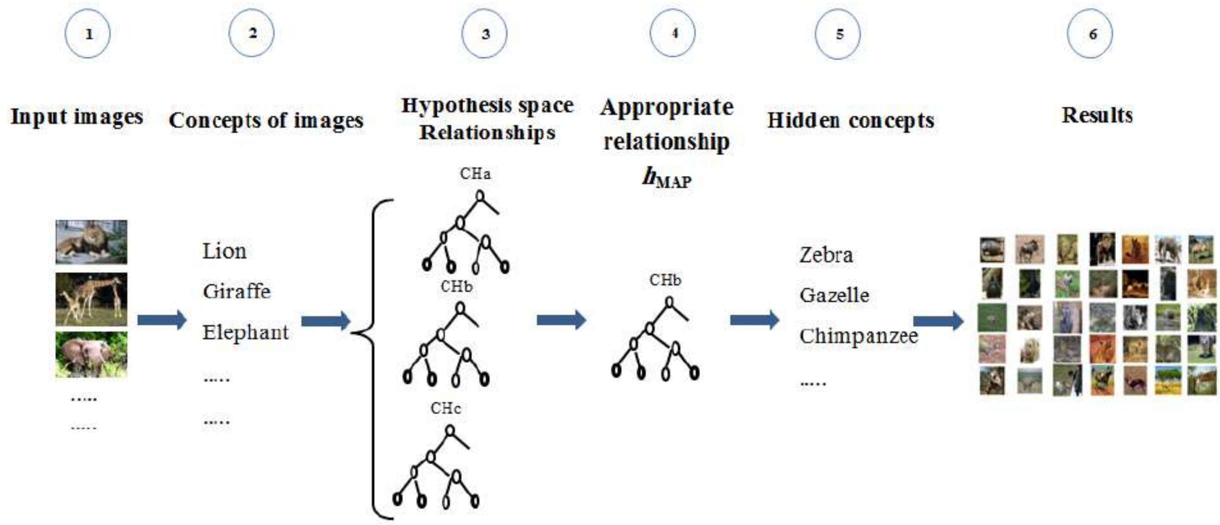



**Figure V.1. Illustrates the main steps of our generalization scheme.**

Hereafter, we give more details about our generalization scheme which consists in six steps.

## V.2.1. Input images (formulation query)

Our system shows the user some sample images from dataset (i.e., user interface) form dataset used in our work as represented in Figure V.2. The user has to select some images example (2 to 5 images) that represent his needs to formulate query, so the query contain several image, as we maintained before this query it is the query by semantic examples QBSE.

**Figure V.2. User interface of our system.**

### V.2.2. Concepts of images

In the dataset used each image is labeled with a keyword, we use Image Net dataset this collection annotated from Word Net. ImageNet is an image dataset organized according to the WordNet hierarchy. Each meaningful concept in WordNet, possibly described by multiple words or word phrases, is called a "synonym set" or "synset". There are more than 100,000 synsets in WordNet, majority of them are nouns (80,000+). In ImageNet, we aim to provide on average 1000 images to illustrate each synset. In our work we use 100 synset from Image Net dataset.

After the user formulates his query, our system has to extract the concepts of each image in the query, those concepts we called *Concept Query*, as outlined in Figure V.3.


**Figure V.3. Images and their corresponding concepts.**

### V.2.3. Hypothesis space (Relationships)

The next step is to create the *Hypothesis space*, after finding *Concepts Query* our system starts by searching all the relationships between the query concepts. All relationships between the *concepts query* in all kinds of concepts hierarchy are called *Hypothesis Space*. As represented in Figure V.4.

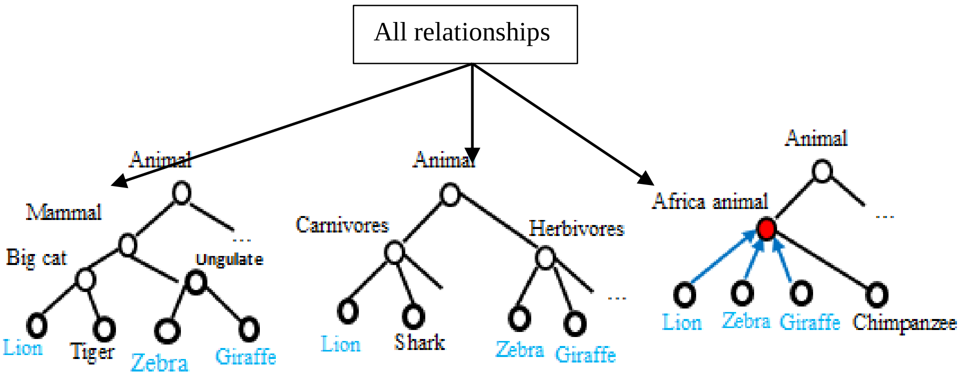



**Figure V.4. All possible relationships in three concepts hierarchy.**

### V.2.4. Finding the appropriate relationship ($h_{MAP}$)

After creating the *hypothesis space* our system has to find the appropriate relationship that groups those concepts. We compute the posteriori probability of each hypothesize in the *hypothesis space* H, The maximum a posteriori can be used to find this appropriate relationship. Figure V.5 represent the appropriate relationship between the concepts query.

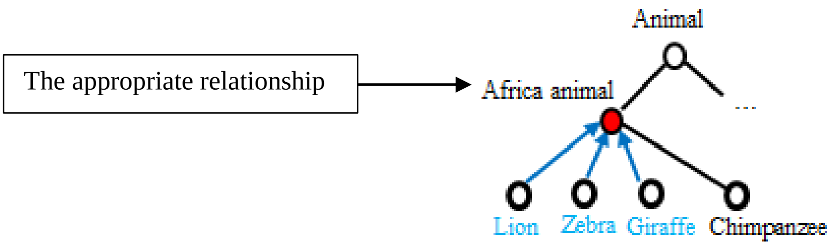



**Figure V.5. Finding the appropriate relationship.**

## V.2.5. Hidden concepts

To cover all images the user needs, we have to extract the *Hidden concepts* which are not appear in the query, *Hidden concepts* are the concepts that are linked with the *concepts query* by the appropriate relationship selected in the concept hierarchy, as depicted in Figure V.6.

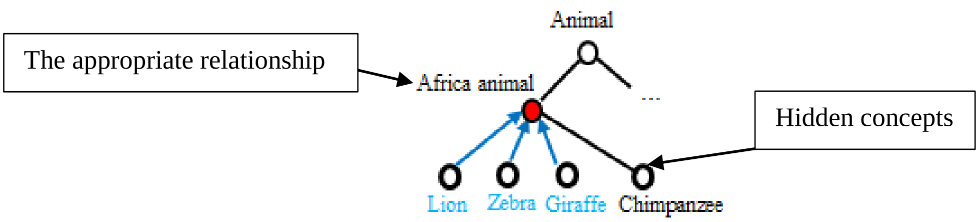



**Figure V.6.The hidden concepts; Concepts that did not appear in the query, but linked its relationship with the query concepts.**

### V.2.6. Results

Finally our system searches all images labeled with *concept query* and *hidden concepts*, and shows results to the user (Figure V.7). So the results include:

- Images annotated explicitly by the concepts of the query.
- Images of the same class as the images of the query, according to the selected CH.
- The images whose concepts are related to the concepts of the query by the chosen relationship.
- Images Annotated with *Hidden concepts* that he has discovered.

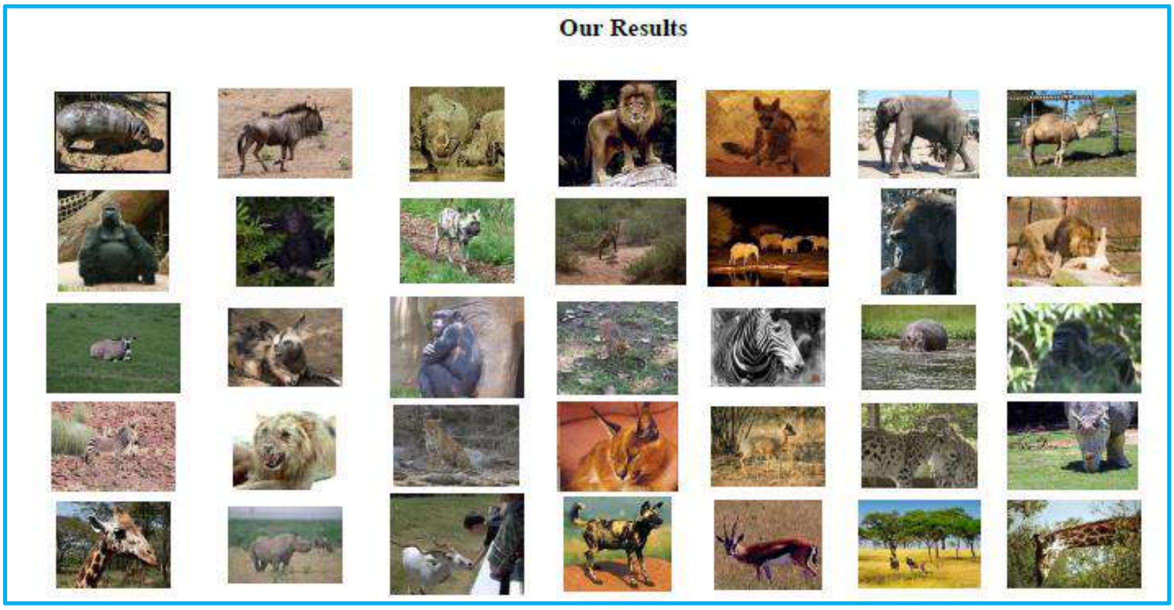



**Figure V.7.Results of our approach.**

# V.3. Formal details of our algorithm

## V.3.1. Create the hypothesis space H

After the query concepts ***X*** are recognized. The algorithm starts by searching for all the relationships that combine the concepts, in all concepts Hierarchies CHs. We called all possible relationships between concepts query "the hypothesis space" ***H***. Each hypothesis $h_i$ is considered the candidate to be the appropriate concept **C**.

The creation of the hypothesis space is done according to the following equation:

$$P(h \mid X) \propto P(h)P(X \mid h) \qquad (6)$$

Such that *P(h|X)* is the posterior probability, *P(h)* the prior probability and *P(X|h)* the likelihood. The prior P(h)*P(h)* of the hypothesis is defined according to the Erlang distribution

$$P(h) \propto \left(|h| / \sigma^2\right) \exp \left\{-|h| / \sigma\right\} \qquad (7)$$

Where |h| is the size of the hypothesis h (number of leaf nodes) and σ parameter is the mean size of the basic level hypotheses.

The likelihood is determined by the assumption of randomly sampled positive examples. In the simplest case, each example in X is assumed to be independently sampled from a uniform density over the concept C. For n examples we then have:

$$p(X \mid h) = \begin{cases} \left[\dfrac{1}{|h|}\right]^n & \text{if } x_1,\ldots,x_n \in h \\ 0 & \text{if any } x_i \notin h \end{cases} \qquad (8)$$

We calculate the posterior probability $P(h|X)$ of each hypothesis $\boldsymbol{hi}$ within each CHs. When the posterior probability $P(h|X)$ of the hypothesis $\boldsymbol{hi}$ is 0, we make it out of the hypothesis space $\boldsymbol{H}$. If the probability is greater than 0, this hypothesis hi is within the space of hypotheses $\boldsymbol{H}$. In this way, we get all the possible possibilities for the algorithm to be studied in the next step.

### V.3.2. Finding the Maximum a posterior $\boldsymbol{h}_{\mathbf{MAP}}$

After forming the hypothesis space $H$, we choose the hypothesis which has the maximum a posteriori. We have, therefore, identified the appropriate concept **C** for this query. We find the Maximum a posteriori $\boldsymbol{h}_{\mathbf{MAP}}$ according to equation:

$$h_{MAP} = \underset{h \in H}{\operatorname{argmax}} P(X \mid h) P(h) \tag{9}$$

### V.3.3. Select the appropriate CH and the appropriate C :

The appropriate C is the Maximum a posterior $\boldsymbol{h}_{\mathbf{MAP}}$ and the appropriate CH is the belong of the C .

### V.3.4. Finding the hidden concept $\mathbf{C}_{\mathbf{i}}$

The hidden concepts are the concepts under C and which didn't appear in the query and belong the same class with the concepts query.

The steps of our algorithm are summarized in Algorithm 1.

**Algorithm 1: Generalization of query**

**Begin**

1: **INPUT:** X = {x1, x2, …xn}

2: Compute posterior probability $P(h|X)$ of all hypotheses h in CHa, CHb and CHc according to equation :

$$P(h \mid X) \propto P(h)P(X \mid h)$$

3: Find the Max a posteriori $h_{MAP}$ according to equation:

$$h_{MAP} = \underset{h \in H}{\operatorname{argmax}} P(X \mid h)P(h)$$

4: Select appropriate CH and the C.

5: Find Hidden Ci

(The concepts under C and which didn't appear in the query)

6: **OUTPUT:** Result of images Ii annotated by all leaf nodes under the concept C.

**End.**

## V.4. Presentation of our concept hierarchies

A human can search for images from all fields according to his needs, such as medical field, scientific field, technology or animal field. Computer system should help human to retrieve images that satisfy their needs through query. We must therefore expand the concepts in several demands. So that we can bring the engine closer to the user's thinking. In this thesis, we chose the field of animals in order to clarify the idea more. Animals have several different relationships in terms of family type, living place and diet.

In our framework, we use three kinds of concept hierarchies to expand the scope of user understanding, where each hierarchy groups concepts according to a specific relationship. The database used here contains animal images from ImageNet, so the relationships are: according family, according diet and according region place. Next, we give details about each of them.

### V.4.1. Concept hierarchy according to family CHa (ImageNet hierarchy)

We use Image Net hierarchy as the first CH, we denote it by $CH_a$. Image Net is a large image database which is based on the WordNet hierarchy. Each concept in WordNet is described by multiple words which are called a "synonym set" or "synset". We have chosen Image Net hierarchy because it has a rich hierarchy of concepts and it assembles millions of images (about ten million images that have been manually annotated). In our work, we are interested by the part which categorizes the animals (Figure V.8)

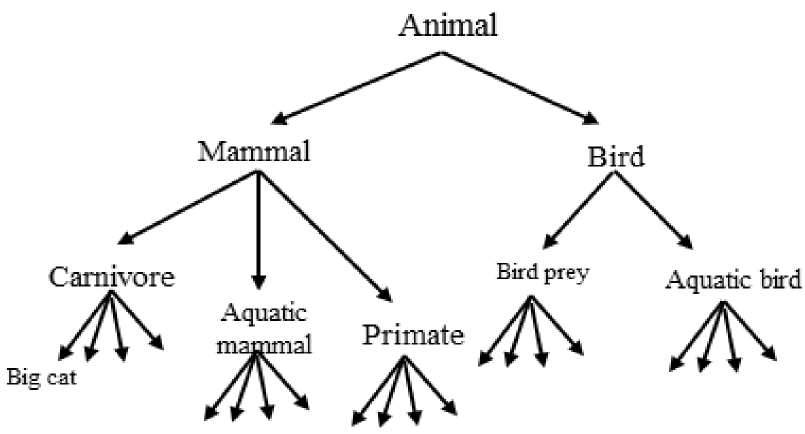



**Figure V.8.Illustration of the concept hierarchy CHa.**

### V.4.2. Concept hierarchy according to diet $CH_b$

In Wikipedia we can find all information about a concept (animal in our dataset) as shown in Figure V.11. We build this type of relationship based on Wikipedia. Our concept hierarchy is built based on the food nature of each "synset" in the dataset as shown in Figure V.9. We denote the current Concept hierarchy by $CH_b$.

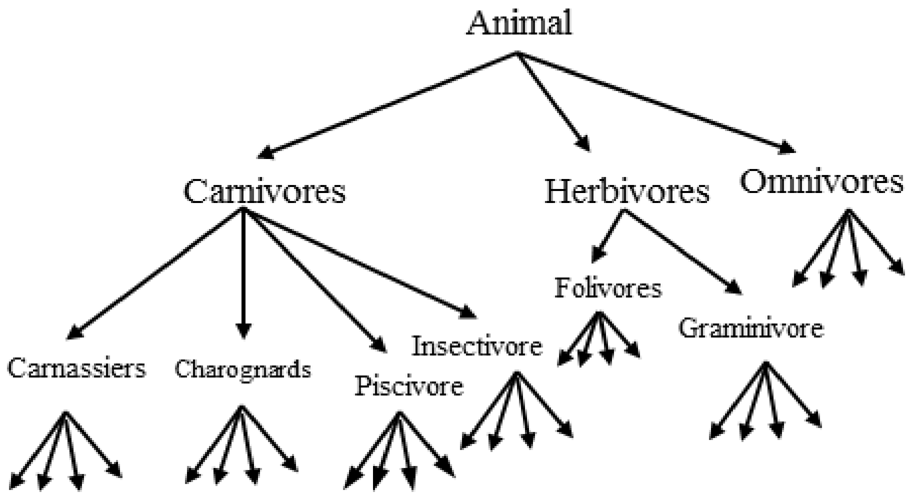



**Figure V.9.Illustration of the concept hierarchy $CH_b$.**

### V.4.3. Concept hierarchy according to region of living CHc

The region of living is a synset within ImageNet, thus, we adopt a CH that groups concepts according to region of living (Africa animal, Asia animals, Europa animals, Australian animals, Arctic and Antarctic animals) as depicted in Figure V.10. We denote it by CHc. Also we create this concept hierarchy based on Wikipedia. In Figure V.11 the example of concept "**Ice bear"** we can find the region of living "**Arctic"** from Wikipedia.

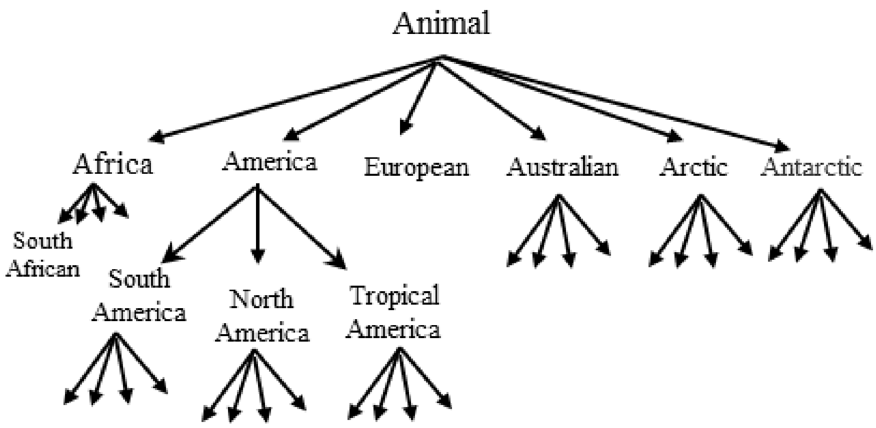



**Figure V.10.Illustration of the concept hierarchy CHc.**

# Polar bear

From Wikipedia, the free encyclopedia
(Redirected from Ice bear)

*This article is about the animal. For other uses, see Polar bear (disambiguation).*
*"Ice bear" redirects here. For the We Bare Bears character, see Ice Bear. For other uses, see Ice Bears (disambiguation).*

The **polar bear** (*Ursus maritimus*) is a hypercarnivorous bear whose native range lies largely within the Arctic Circle, encompassing the Arctic Ocean, its surrounding seas and surrounding land masses. It is a large bear, approximately the same size as the omnivorous Kodiak bear (*Ursus arctos middendorffi*).[5] A boar (adult male) weighs around 350–700 kg (772–1,543 lb),[6] while a sow (adult female) is about half that size. Although it is the sister species of the brown bear,[7] it has evolved to occupy a narrower ecological niche, with many body characteristics adapted for cold temperatures, for moving across snow, ice and open water, and for hunting seals, which make up most of its diet.[8] Although most polar bears are born on land, they spend most of their time on the sea ice. Their scientific name means "maritime bear" and derives from this fact. Polar bears hunt their preferred food of seals from the edge of sea ice, often living off fat reserves when no sea ice is present. Because of their dependence on the sea ice, polar bears are classified as marine mammals.[9]

Because of expected habitat loss caused by climate change, the polar bear is classified as a vulnerable species. For decades, large-scale hunting raised international concern for the future of the species, but populations rebounded after controls and quotas began to take effect.[10] For thousands of years, the polar bear has been a key figure in the material, spiritual, and cultural life of circumpolar peoples, and polar bears remain important in their cultures. Historically, the polar bear has also been known as the **white bear**.[11]

Polar bear
Temporal range: Pleistocene-recent[1]

Conservation status

Extinct — Threatened — Least Concern
EX EW CR EN VU NT LC
Vulnerable (IUCN 3.1)[2]

Scientific classification

| | |
|---|---|
| Kingdom: | Animalia |
| Phylum: | Chordata |
| Class: | Mammalia |
| Order: | Carnivora |
| Family: | Ursidae |
| Genus: | *Ursus* |
| Species: | ***U. maritimus*** |

Binomial name

**Subspecies**

†*Ursus maritimus tyrannus*(?)[4]

Polar bear range

**Figure V.11 The information about the synset Polar bear (Ice bear) in Wikipedia.**

## V.5. Generalizing queries in our approach

Accurate and effective generalization and the query analysis have a fundamental role for obtaining excellent results. That is why we are focusing on this point, because of its high importance in our work. We can summarize our generalization of the query in three basic steps:

**1- Refinement of the query:**

In this first step, we will analyze the concepts chosen by the user to determine what exactly he is looking for. The result of this step is a set of concepts that can belong to different levels of abstraction in different CHs.

**2- The generalization of concepts:**

This step uses the result of the first step. We use different CH to find the relationship between concepts. Further, the result of this step is the relationship between the concepts of the query.

**3- Discover the hidden concepts:**

The presence of two or more concepts in the query allows us to discover new concepts, for example:

- Table and chair involve office.
- Table and spoon involve restaurant.

This step uses the selected relationship in the second step to find the hidden concepts which have a relationship with the concepts of the query. Finally our algorithm returns the relevant images (the images which are annotated with the concepts query and hidden concepts) to the user.

In our case, the system presents a sample of images to the user, and then the user selects images supposed to be similar to what he is looking for (Query by Semantic Examples QBSE). Our proposed approach uses, thereafter, the annotations assigned with those images in order to discover the relationship between the concepts contained in the query and then extract the hidden concepts.

The obtained results of the queries generalizing Q1, Q2 and Q3 in CHa, CHb, and CHc respectively are explain how our proposed approach is working.

Analysis of the Query 1:

Query 1 contains 3 images (see Figure V.12), we have 3 concepts; Image 1 labeled with the concept "Lion", Image 2 labeled with the concept "Zebra" and Image 3 labeled with the concept "Elephant". The Concepts Query is X= {Lion, Zebra, Elephant} with n=3 (Number of the positive examples).

*Image 1* *Image 2* *Image 3*

**Figure V.12. Illustration of the Query 1**

Hypothesis space H:

We create the hypothesis space from the three CH in our dataset we find the following hypothesis:

- $h_1$: Animal from the $CH_a$
- $h_2$: Mammal from the $CH_a$
- $h_3$: Africa animals from the $CH_c$

There is no relationship between query concepts in the $CH_b$ (according of diet) because Lion is a Carnivore animal, Zebra and Elephant are Herbivores animals.

Size of each hypothesis |h|

The size of the hypothesis is the number of leaf nodes or son nodes. Through the concept hierarchies used in the proposed approach we find the flowing size:

- |Animal|=100
- |Mammal|=86
- |Africa animals|=15

The next step calculates the posteriori probability $P(h|X)$ of each hypothesis as illustrated in Table 1 .

**Table 1.Generalization of the query Q1 in each Concept hierarchy**

| **Concept hierarchy** | Hypothesis h*h* | Posteriori probability $P(h|X)$ |
|---|---|---|
| **CHa** | Mammal | 0.56 |
| | Animal | 0.23 |
| **CHb** | No relation matched | / |
| **CHc** | Africa animals | 0.96 |

Maximum a Posteriori hypothesis $h_{MAP}$ :

Through the results given by Table 1, the maximum a posteriori hypothesis of the Query 1 is: $h_{MAP}$= Africa animals.

Hidden concepts: are the concepts that situated under the concepts of “Africa animals”

Chimpanzee, Gnu, Gorilla, Gazelle … etc.

Figure V.13 presents the results of query 1 that contain all the images annotated with concepts of "Africa animals".

**Figure V.13. Results Illustration of the Query 1.**

Analysis of the Query 2:

Query 2 contains 5 images (see Figure V.14), we have 5 concepts; Image 1 labeled with the concept "Gazelle", Image 2 labeled with the concept "Elk", Image 3 labeled with the concept "Two-toed Sloth", Image 4 labeled with the concept "Elephant" and the final image is labeled with the concept "Gnu". The Concepts Query is X= {Gazelle, Elk, Two-toed Sloth, Elephant, Gnu} with n=5.

Image 1 Image 2 Image 3 Image 4 Image 5

**Figure V.14. Illustration of the Query 2.**

Hypothesis h

- $h_1$:Animal
- $h_2$:Mammal
- $h_3$:Herbivores

Size of each hypothesis |h|

- |Animal|=100
- |Mammal|=86
- |Herbivores|=15

The calculation of the posterior probability $P(h|X)$ of each hypothesis of the Query 2, is given in Table 2.

**Table 2**. Generalization of the query Q2 in each Concept hierarchy

| Concept hierarchy | Hypothesis h*h* | Posterior probability $P(h|X)$ |
|---|---|---|
| **CHa** | Mammal | 0.56 |
| | Animal | 0.23 |
| **CHb** | Herbivores | 0.86 |
| **CHc** | No relation matched | / |

Maximum a posteriori hypothesis $h_{MAP}$ : Through the results in the Table 2, the Maximum a posteriori hypothesis of the Query 2 is:

$h_{MAP}$= Herbivores

Hidden concepts are: The rest of the Herbivores animals.

Giraffe, Hippopotamus, Gorilla, Koala, Caribou.

Figure V.15 shows the results of query 2 that contain all the images annotated with concepts of "Herbivores animals".

**Figure V.15. Results Illustration of the Query 2.**

Analysis of Query 3:

Concepts Query

Query 3 contains 4 images (see Figure V.16), we have 4 concepts; Image 1 labeled with the concept "Leopard", Image 2 labeled with the concept "Ocelot", Image 3 labeled with the concept "Tiger" and the final Image is labeled with the concept "Cougar". The Concepts Query is X= {Leopard, Ocelot, Tiger, Cougar} with n=4.


**Figure V.16. Illustration of the Query 3.**

Hypothesis h

- $h_1$:Animal
- $h_2$:Mammal
- $h_3$:Feline
- $h_4$:Carnivores

Size of each hypothesis |h|

- |Animal|=100
- |Mammal|=86
- | Feline |=5
- |Carnivores|=34

The posteriori probability $P(h|X)$ calculation of each hypothesis of the Query 3 is given in Table 3.

**Table 3 . Generalization of the query Q3 in each Concept hierarchy**

| Concept hierarchy | Hypothesis hh | Posterior probability $P(h|X)$ |
|---|---|---|
| **CHa** | Mammal | 0.56 |
| | Animal | 0.23 |
| | Feline | 0.87 |
| **CHb** | Carnivores | 0.55 |
| **CHc** | No relation matched | / |

Maximum a Posteriori hypothesis $h_{MAP}$: Through the results given by Table 3, the Maximum a Posteriori hypothesis of the Query 3 is:

$h_{MAP}$ = Feline

Hidden concepts: the rest of the Feline animals.

Lion, Jaguar, Panther, Lynx.

Query 3 Results:

Figure V.17 shows the results of query 3 that contain all the images annotated with concepts of "Feline animals".

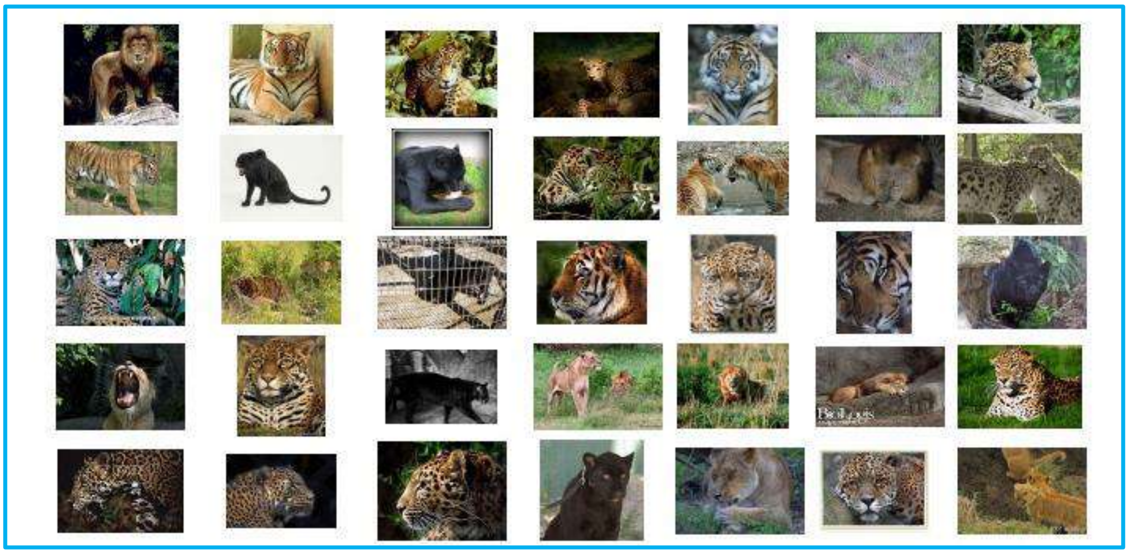


**Figure V.17. Query 3 results Illustration.**

Through the given examples, we find that the algorithm is capable to generalize in any concept hierarchy and find the appropriate relationship between concepts whatever the kind of the relationship. Hence, the obtained results prove the effectiveness and efficiency of our algorithm in user intention understanding.

## V.6. Conclusion

In this chapter, we have presented the details of the first solution. We used the Bayesian model of generalization in multiple concept hierarchy to overcome the raised issue. First, we have created the hypotheses space to find all relationships between concepts. Then, we have computed the posterior probability of each hypothesis then choosing the appropriate hypothesis to discovering the appropriate generalization, after that we have discovered the hidden concepts for exploit the query expansion method. Further, we have applied this proposed approach in the context of image retrial in order to understanding user's intention and alleviate the intention gap and the semantic gap. Finally, we have enhanced the effectiveness of the algorithm by giving examples of queries with the details of the generalization. In the next chapter, we will demonstrate the effectiveness of our generalization and we compare our findings results with previous works.

# CHAPTER VI. EVALUATION OF OUR GENERALIZATION IN IMAGE RETRIEVAL USING MULTIPLE CONCEPT HIERARCHIES

## VI.1. Introduction

In the previous chapter we have presented the details of the first solution. In this chapter we will demonstrate and prove the effectiveness of this solution to overcome the raised issues. First we present the dataset used in this work, than we will explain the senior of the experiments. We then evaluate the overall performance of the system, then we show the finding results and we compare with the state-of the art. Finally, we analyzing and discussing the obtained results.

## VI.2. Experimental setup

### VI.2.1. Dataset

In order to demonstrate the effectiveness of the proposed approach, we carried out our experiments on ImageNet dataset (Deng et al., 2009). It contains 14,197,122 images in 21,841 categories indexed according to the hierarchy of Word Net (Fellbaum, 1998). A category in ImageNet corresponds to a synonym set (synset) in WordNet. ImageNet covers a subset of the nouns of WordNet, organized in 12 high level categories, (e.g. animal, Plant, instrumentality...) as shown in Figure VI.1.

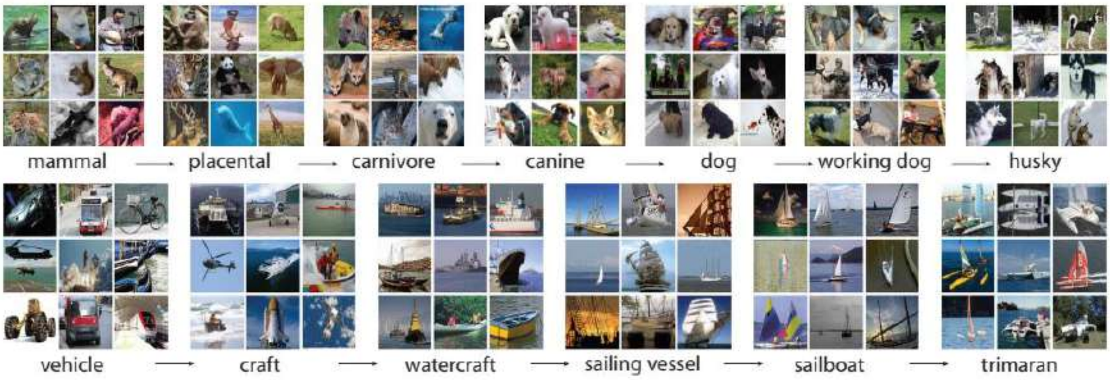



**Figure VI.1. A part of two Root to Leaf branches of ImageNet, Mammal and Vehicle subtrees (**Deng et al., 2009**).**

In the present work, we focus on the animal category. We select, 100 synsets of animals to create our dataset which is made up of 111,135 images (we choose those synset to formulate three concept hierarchy each synset have a relationship in all concept hierarchies) Figure VI.2 show example of synset (leaf nod) in Image Net and her information and all corresponding images.

These images are organized according to three hierarchies as we maintained in the previous chapter, one is that of ImageNet According to family $CH_a$ and we add two others which are (According to diet $CH_b$ and According to region of living $CH_c$) as described above.

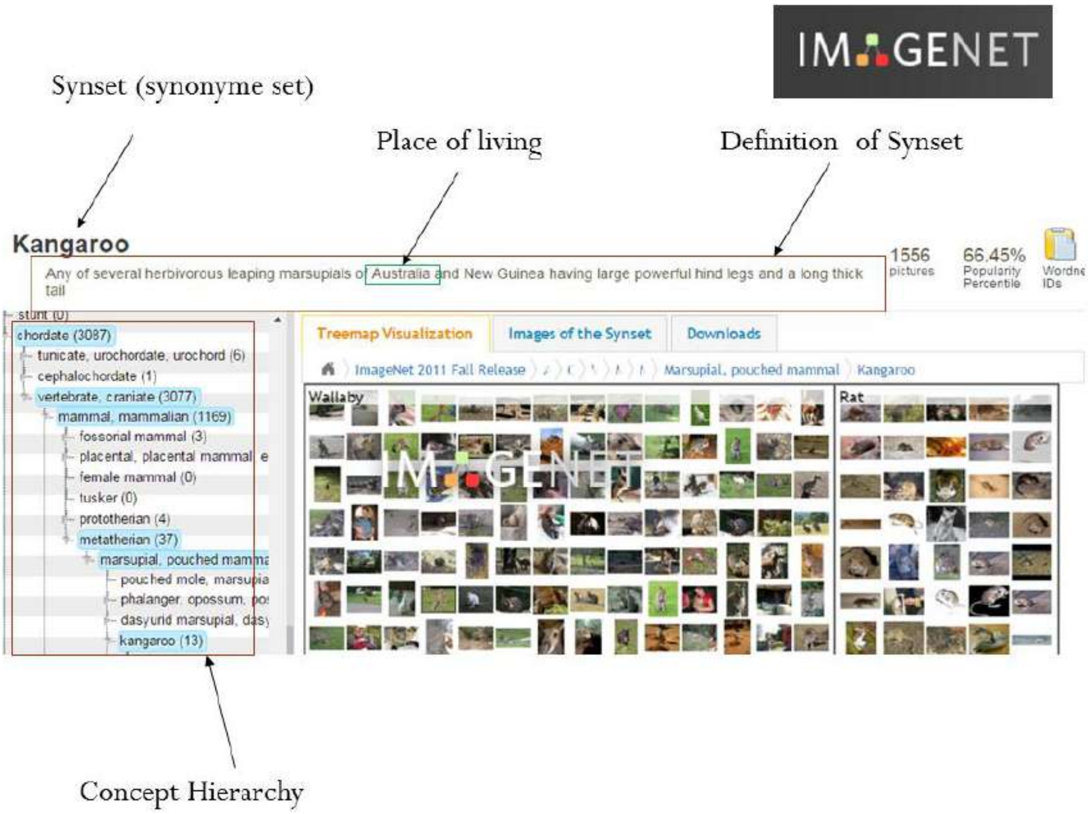



**Figure VI.2. Representation of Leaf nod in ImageNet, Kangaroo.**

As we maintained before, we study each concept (synset) separately. We have to know all its details, his family, where he lives and what he feeds. Then we classify them into groups that share common relationships. Then we divide the aggregates into three categories to get three different classifications as demonstrated in Figure VI.3.

It can be added another classification for example according on how they live in groups or individually …. etc.

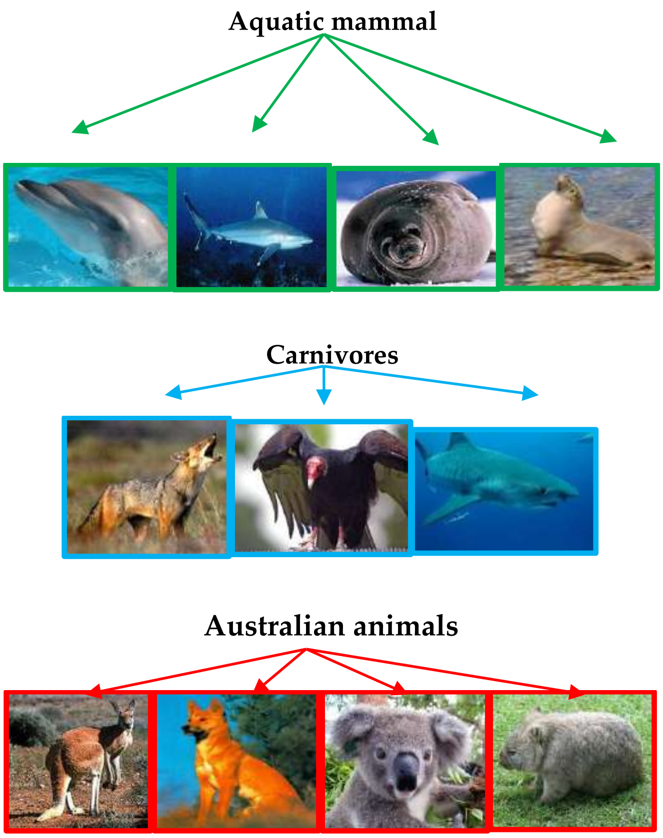



**Figure VI.3. Some examples of the relationship in different concept hierarchies.**

### VI.2.2. Scenario of Experiments

To perform experiments, we have invited 20 participants. The scenario of the experiment is started by supplying some example images. Each participant supplies a query made up of 2-5 positive images, Figure **VI.5** represent some example queries formulate by the participants. Our approach try to understanding what user want from this query. To achieve a better understanding of user, we generalize the queries in the three proposed concept hierarchies. The experiments conducted with 20 participants demonstrate the effectiveness of our approach. The scenario of experiments with each participant is shown in Figure VI.4.


**Figure VI.4. Some query formulate by the participants.**

This test allows us to truly investigate the ability of our method in meeting human thought and intentions. We compare the performance of the proposed method with another one from the state of the art.

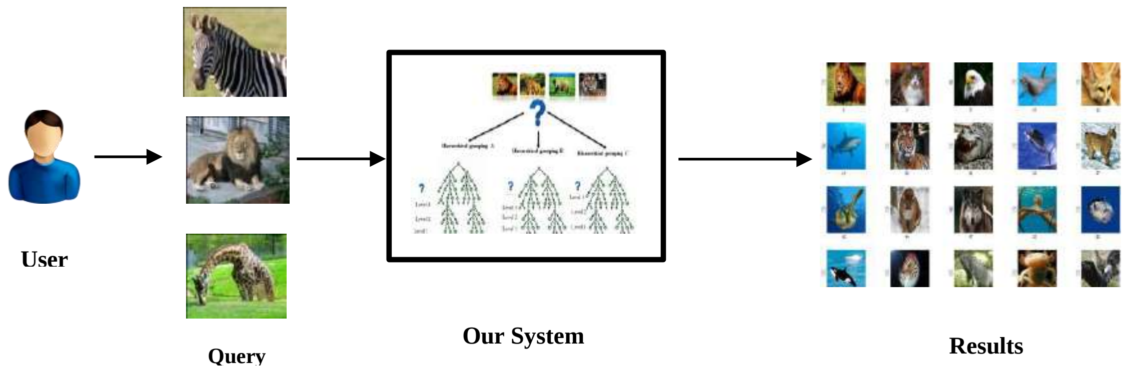



**Figure VI.5. Illustration the senior of our approach.**

### VI.2.3. Evaluation metrics

In order to evaluate our work, we tested it on a collection of ImageNet with different categories of animals. We adopt the corresponding concepts hierarchies, as shown in Figure II.6 (See Chapter II). We carried out many tests from several participants to compare the results with the conventional Bayesian generalization.

The performance of our approach is analyzed, using several performance metrics. Many of the image retrieval systems use precision and recall as the performance metrics. Precision is computed using Equation (10) and recall is calculated using Equation (11).

$$\mathrm{Pr}ecision = \frac{Number\ of\ \ relevant\ retrieved\ \ images}{Number\ of\ \ \mathrm{Retrievaed}\ images} \qquad (10)$$

$$\mathrm{Re}call = \frac{Number\ of\ \ relevant\ retrieved\ images}{Number\ of\ \ \mathrm{relevant\ images}\ in\ dataset} \qquad (11)$$

For the evaluation criterion, we adopt the Mean Average Precision (MAP) which is a metric which takes into consideration the ranking order of the retrieved images. It is defined as:

$$MAP = \frac{\sum_{q=1}^{Q} AvgP(q)}{Q} \qquad (12)$$

Such that is $Q$ the number of queries, and $AvgP(q)$ is the average precision of the query $q$.

The accuracy percentage is also used in analyzing our system. The accuracy of the system is calculated using Equation (13):

$$Accuracy\,\% = \frac{\sum_{i=1}^{T} q_i}{T} \times 100 \qquad (13)$$

Where qi is 1 in Equation (13), if the $i^{th}$ query image retrieve correct resultant images; qi = 0, otherwise. T is the total number of query images.

# VI.3. Experimental results

## VI.3.1. Measuring the overall performance

To provide an objective evaluation of our approach, we launched several queries and measured the Precision and Recall of each query. The obtained results are shown in Figure VI.6, Figure VI.7, Figure VI.8 and Figure VI.9. The precision and recall values for the results obtained by the queries of the 20 participants. The higher the precision and recall values, the better the performance. The total number of images considered in each query is 200.

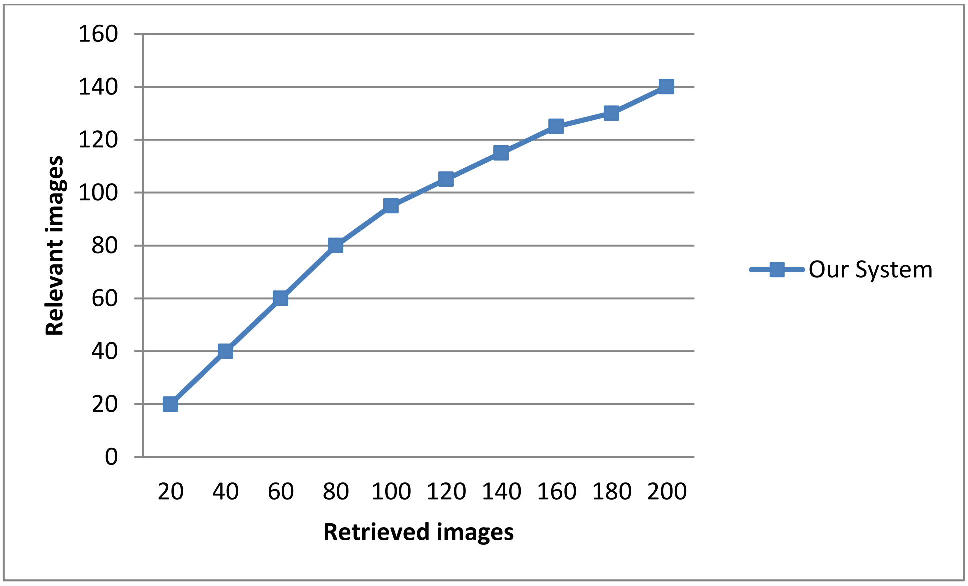



**Figure VI.6. The number of relevant images in top 200 images.**

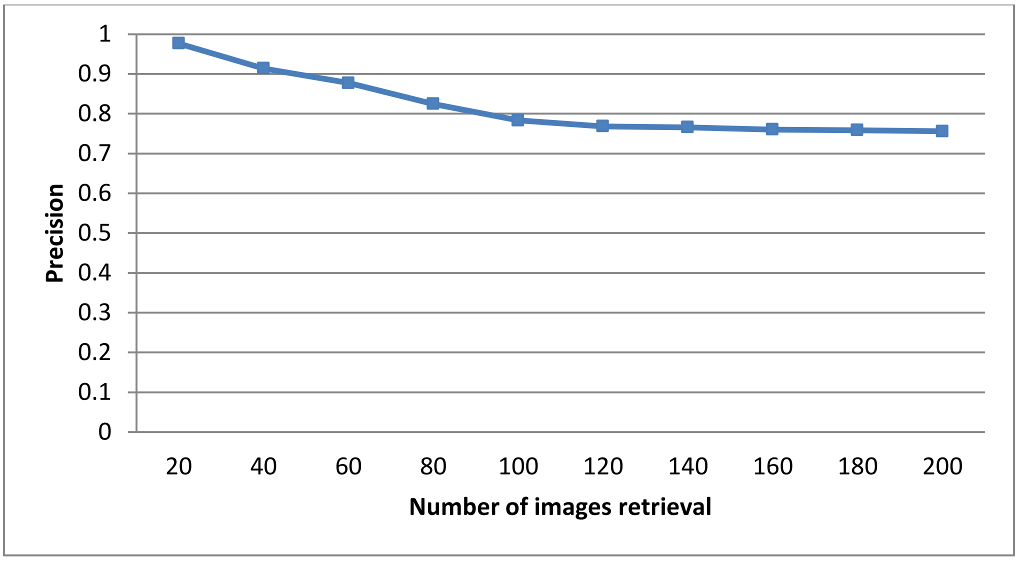



**Figure VI.7. The Precision curve of our algorithm.**

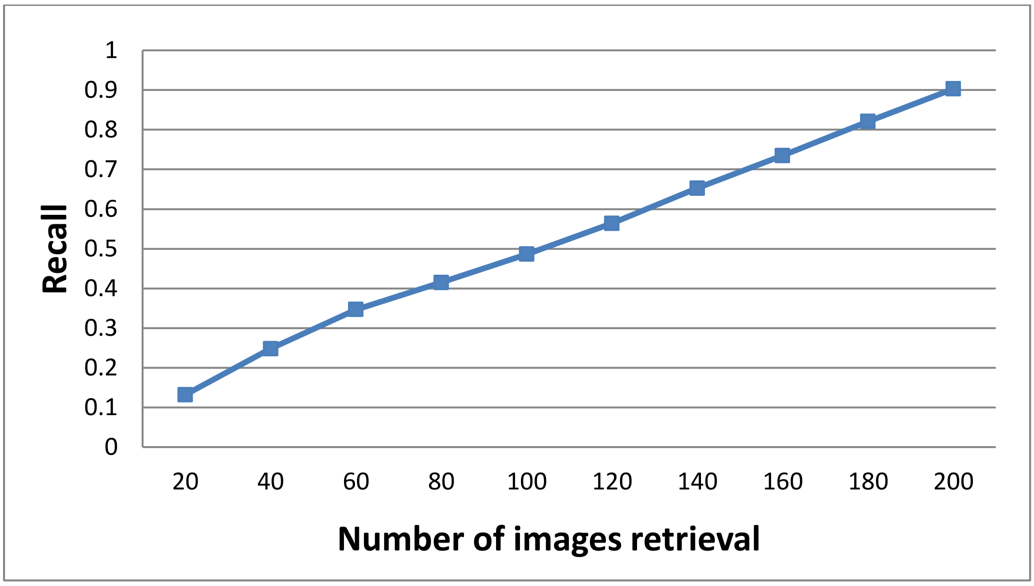



**Figure VI.8. The Recall curve of our algorithm.**

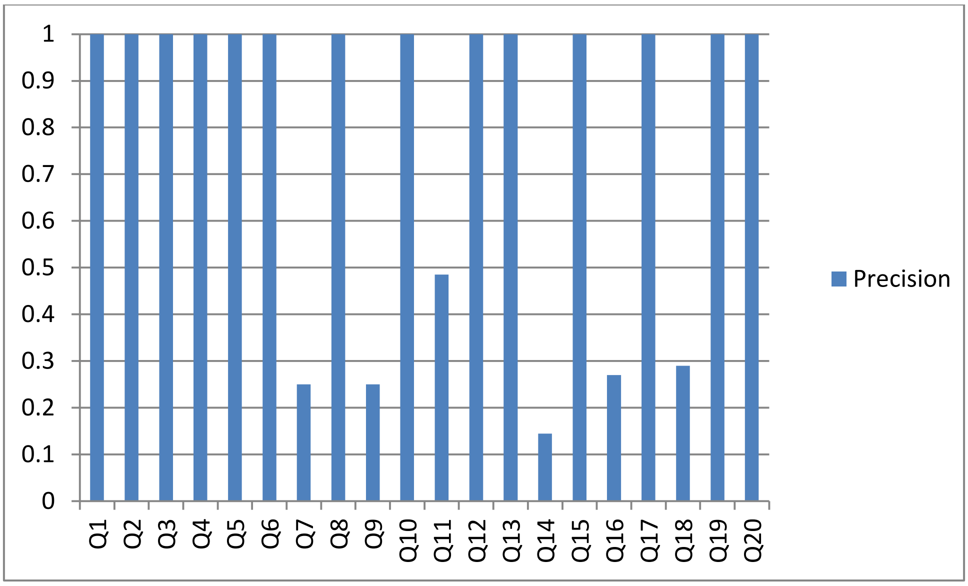



**Figure VI.9. Precision of 20 queries.**

From Figure VI.7, we notice that precision slightly decrease whenever the scope increases. For instance, at a scope equal to 200, we see that the average precision remains relatively high (0.75). From Figure VI.8, we observe that the recall increases whenever the scope increases. Figure VI.6 shows the number of relevant images, and Figure VI.9 illustrates the Precision of 20 queries. Indeed, this confirms the powerfulness and the strength of our approach.

### VI.3.2. Comparison the results with the state of the art:

In this section we compare the performance of the proposed approach with the conventional approach in (Jia et al., 2013). Figure VI.10 shows the number of relevant images retrieved by our and conventional approach and the conventional approach in (Jia et al., 2013). The results show that the proposed method significantly outperforms the conventional approach. This may be attributed to the fact that we haven't restricted ourselves to only one concept hierarchy and we have generalized the query using 3 different hierarchies.

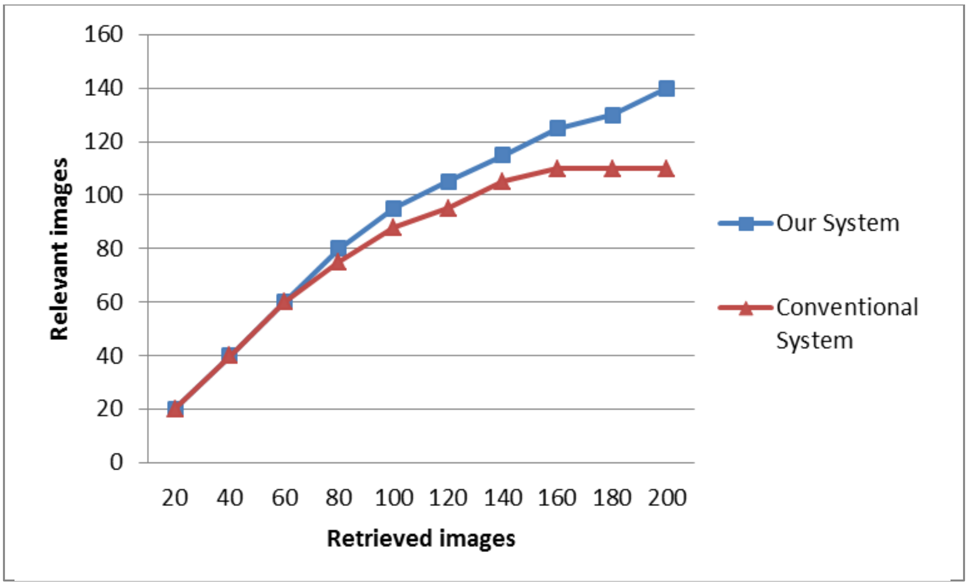



**Figure VI.10.** The number of relevant images in our algorithm and conventional system.

**Table 4. Comparison with state of the art system in terms of MAP.**

| **Methods** | **Conventional approach (2013)** | **Our approach** |
|---|---|---|
| **MAP** | **58** | **75** |

From Table 4, it is significantly that the proposed approach outperforms the conventional approach. It outperformed the Conventional approach with 17%. These achievements are mainly due to the generalization we adopt which used multiple concept hierarchies.

To confirm the strength of the proposed method, we report the precision-scope (Figure VI.11), the recall-scope (Figure VI.12) and precision-recall curves (Figure VI.13) for both our method and the method of (Jia et al., 2013).

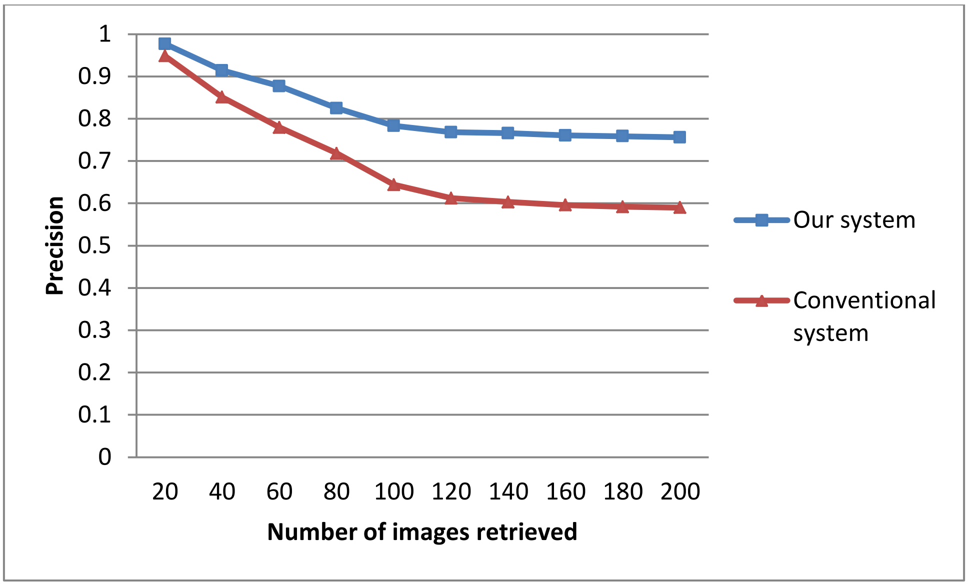



**Figure VI.11. The average Precision curves of conventional approach and our approach.**

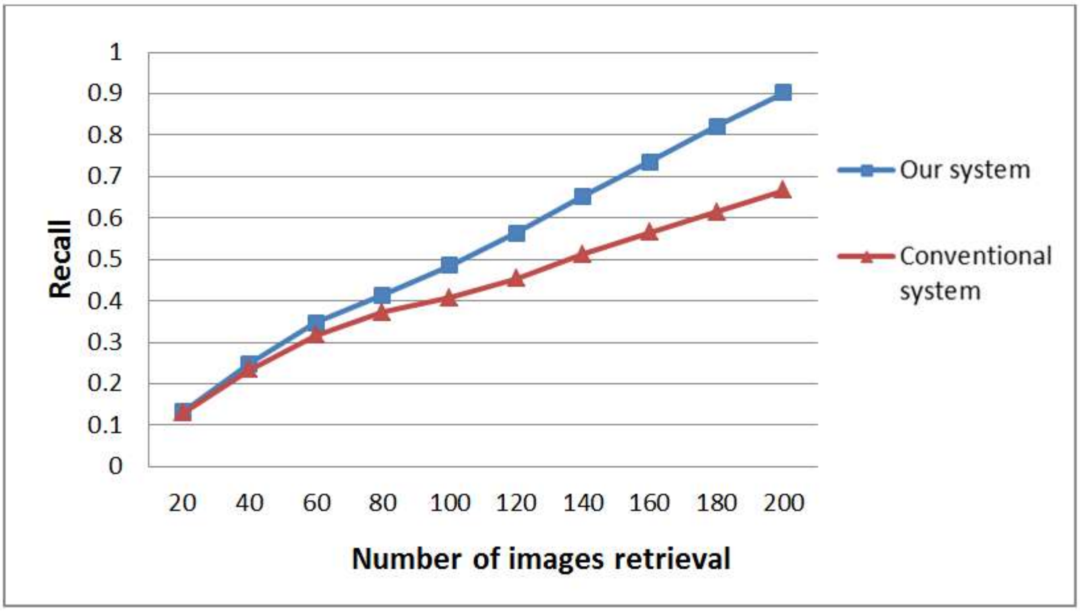



**Figure VI.12. The average Recall curves conventional approach and our approach.**

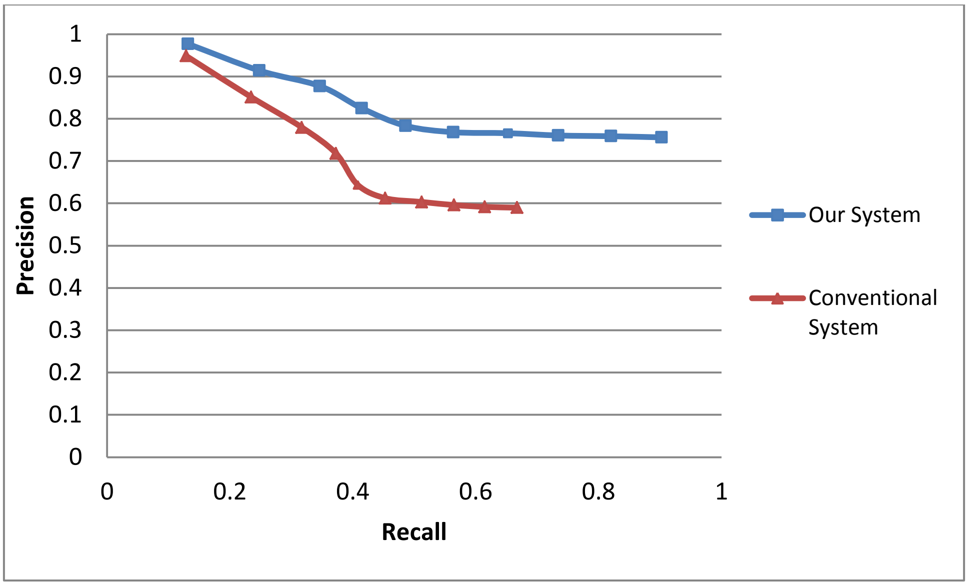



**Figure VI.13. The Precision Recall curve of conventional approach and our approach.**

Figure VI.11 shows the precision curves for all queries. The results show clearly the precision improvement of our approach comparing to the conventional approach which means that the accuracy has improved. Hence, the retrieval of relevant images will be enhanced. It is clearly observed in Figure VI.12 where the recall increases.

The results obtained in Figure VI.13 shows that clearly show that the proposed method significantly outperforms the method in . This indicates that the search engine used in our work has been very successful in understanding the user's intention.

From Table 5, we notice that our approach has significantly outperformed the conventional approach with 37%. We believe that the main reason behind that is our generalization which adopts three concepts hierarchies. This conventional approach isn't capable to deal with the queries out the first concept hierarchy $CH_a$.

**Table 5. Average recognition accuracy yielded by each approach.**

| Method | Conventional approach (Y 2013) | Ours |
|---|---|---|
| **Average accuracy (%)** | **33** | **70** |

We can see that the proposed method overcomes the method in (Jia et al., 2013). In summary, from this experiments we have conducted, we note that the proposed method is capable to detect the appropriate generalization level in the different hierarchies ($CH_a$, $CH_b$ and $CH_c$). Our system can predict what the user wants through the query. This is unlike the existing methods which are limited to a single hierarchy, as we see in Table 6 bellow, comparison the results between Conventional generalization and ours. Some examples queries WhereQ1 generalization in $CH_a$ and Q2, Q3, Q4 and Q5 generalization in $CH_b$ and $CH_c$.

Therefore, our method is capable to understand the user intention and retrieve the targeted images by the user. Experimental results have demonstrated that our method yields better results than those based on a single hierarchy.

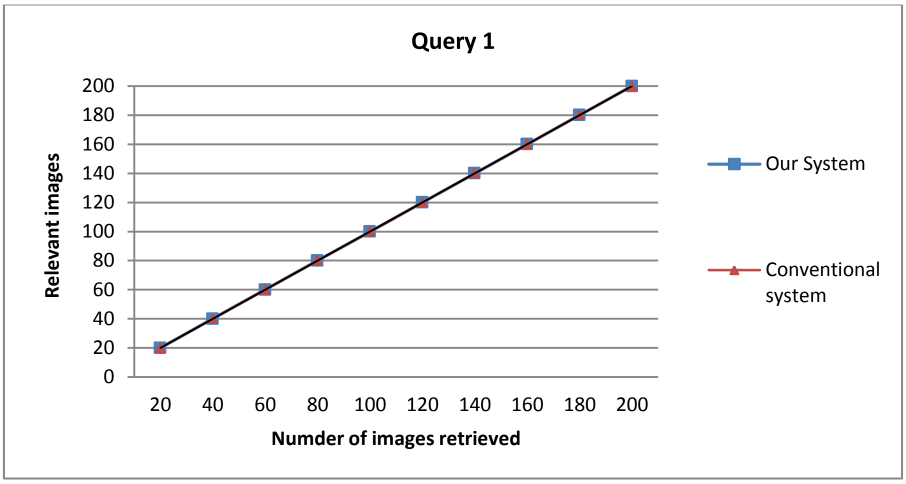
**Table 6. Comparison the results between Conventional approach and ours.**

| Query | User intention | Conventional approach | Proposed approach |
|---|---|---|---|
|  | Birds | Birds ✓ | Birds ✓ |
|  | Africa animals | Mammal ✗ | Africa animals ✓ |
|  | Herbivores | Mammal ✗ | Herbivores ✓ |
|  | Asia animals | Mammal ✗ | Asia animals ✓ |
|  | **Omnivores** | Mammal ✗ | **Omnivores** ✓ |

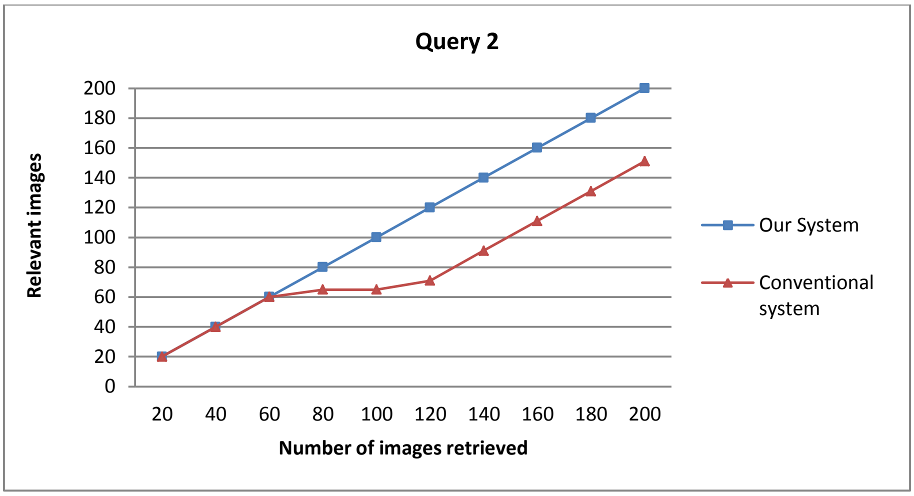
Figure VI.14 demonstrate the details of returned results for queries. This figure plots the number of correct images in top N retrievals versus the total number of images returned in ranking order. From these results is clearly shown that our solution was able to detect relevant images that were ignored by the conventional system.

We find that conventional research was limited to one single concept hierarchy. The results obtained from some examples queries are shown in Figure VI.15.

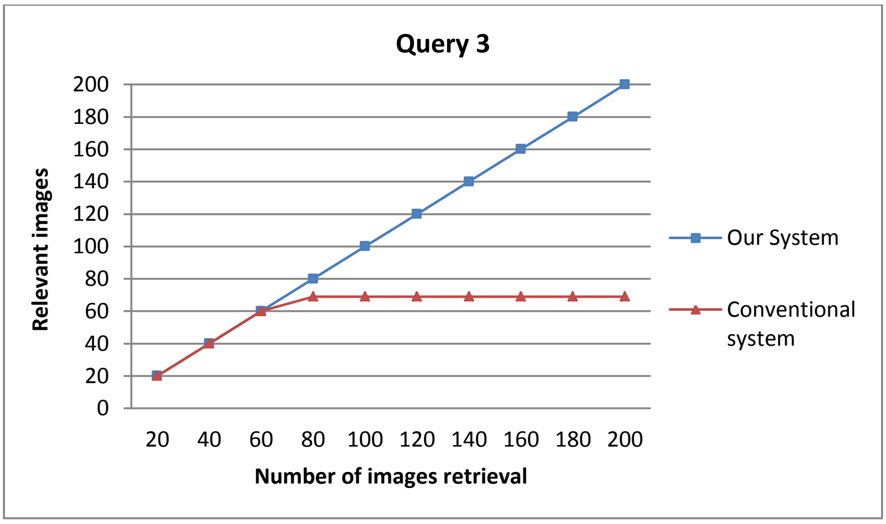
The findings from this study suggest that our algorithm often select the appropriate level of generalization in that different Concept Hierarchies, and able to understanding user intention with better choosing of the concepts. Unlike the conventional formwork is often failed to determine the user's needs in the new added CH. Experimentations demonstrate that our algorithm, which uses multiple hierarchies, yields better result than those based on one single hierarchy. In summary, the experimental results reveal the efficacy of using multiple concepts hierarchies.




Generalization in CHa

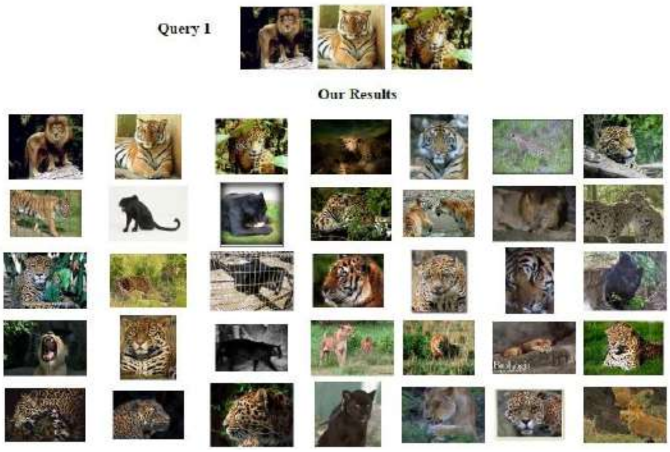



Generalization in CHb




Generalization in CHc

**Figure VI.14. The performance of relevant images in our approach and conventional approach in 3 queries with different CH.**




Result: Generalization in CHa with Relationship (Big cat).


Result: Generalization in CHb with Relationship (Herbivores animals).


Result: Generalization in CHc with Relationship (Africa animals).

**Figure VI.15 . Results of some example queries.**

## VI.4. Conclusion

In this chapter, we have demonstrated the effectiveness of the proposed approach. We have used multiple concept hierarchies to generalize the query and to improve the understanding the user intention. Our system is capable to discover the relationships between concept query, and it is capable to choose the appropriate generalization among several concept hierarchies and also expand the query by discovering hidden concepts. Moreover, Experiments show that the proposed method significantly outperforms the conventional approach and give the best results in image retrieval.

# CHAPTER VII.OUR SECOND CONTRIBUTION : A NEW METRIC FOR MEASURING SEMANTIC SIMILARITY BETWEEN A SET OF CONCEPTS.

## VII.1. Introduction

Human has the ability to know whether two concepts have a great similarity or are not similar at all, this is due to his experience and also his knowledge. For example, Human can realize that both car and travel are closer to each other a lot, and he can also realize that both car and animal have no similarity between them, where they are so far from each other. This decision is intuitive for humans. This is a challenge task for machines to simulate judgment process of humans. Without the formulation contextual knowledge surrounding each concept and its relationships it will be difficult to achieve. Previous searches on this issue have focused mainly on measuring the semantic similarity between either large documents or individual concepts. The objective of semantic similarity methods is to create a model that is closely to human judgment.

We use the semantic similarity in multiple concept hierarchy to find the appropriate relationship among concepts, the appropriate concept hierarchy and the hidden concepts. To do so, we compute the SS among concepts of the query in each CH to discovering the relationships between concepts. Then, we chose the appropriate relationship that has the max SS among the concepts. Finally we extract the hidden concepts. It worth mentioning that users may make mistakes during query formulation, we therefore focus on the elimination of the noisy concept.

## VII.2. Semantic similarity SS

Over years, great efforts have been devoted to measure the semantic similarity among concepts based on information content IC , Such as Resnik(Resnik, 1995), Lin (Lin, 1998) and Jiang and Conrath (Jiang & Conrath, 1997), and other(Rada et al., 1989) , (Z. Wu & Palmer, 1994), (Leacock & Chodorow, 1998) based on edge Edge-based Methods.

We give below a short depiction to every one of these measurements:

Resnik (Resnik, 1995) defined the similarity between two concepts in WordNet as the negative log likelihood of the information content (IC of LSO **L**owest **S**uper **O**rdinate).

$$sim_R(c_1,c_2)=-\log(p(lso(c_1,c_2))) \quad (14)$$

Jiang-Conrath(Jiang & Conrath, 1997)subtracts the IC of the LSO from the sum of the IC of the individual concepts, which gave the following dissimilarity measure :

$$Dist_{JC}(c_1,c_2)=2\log(p(lso(c_1,c_2)))-(\log(p(c_1))+\log(p(c_2))) \quad (15)$$

Lin (Lin, 1998) defined the similarity as the ratio of information content between LSO and both concepts.

$$sim_L(c_1,c_2)=2\times\log(p(lso(c_1,c_2)))/\log(p(c_1))+\log(p(c_2)) \quad (16)$$

The measure of Rada (Rada et al., 1989) is the first to use the distance between the nodes corresponding to the two meanings on hyponymic and hyperonymic links:

$$Sim_{Rada}(s_1, s_2) = d(s_1, s_2) = N_1 + N_2 \qquad (17)$$

The terms found deeper in the taxonomy being always closer than the more general terms, (Z. Wu & Palmer, 1994) propose to take into account the distance between the most specific common ancestor and the root to remedy it.

$$Sim_{WuP} = \frac{2 \cdot N_3}{N_1 + N_2 + 2 \cdot N_3} \qquad (18)$$

(Leacock & Chodorow, 1998) also rely on the measure of Rada, but instead of normalizing by the relative depth of taxonomy with respect to the senses, they choose a normalization with respect to the total depth of taxonomy D and normalize with a logarithm:

$$Sim_{lch} = -\log \frac{length}{2 * D} \qquad (19)$$

Where length is the *length* of the shortest path between two concepts using node counting and D is the maximum depth of the taxonomy.

The principle of taxonomic distance measurements is to count the number of arcs separating two directions in taxonomy Figure VII.1 .

(Z. Wu & Palmer, 1994) represent the relationship of any two meanings C1 and C2 in taxonomy with respect to their most specific common sense C3 and with respect to the root of taxonomy.

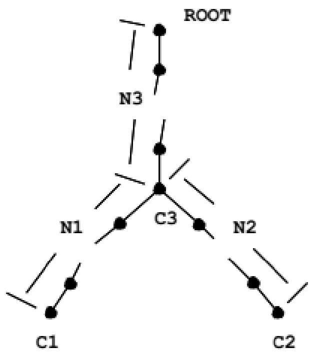



**Figure VII.1.The concept similarity measure (**Z. Wu & Palmer, 1994**)**

All of these methods consider the similarity between two concepts only and based in one type of ontology (WordNet). In this chapter, we propose a new approach to obtain the SS among multiple concepts rather than two only. We also based on three ontologies (concept hierarchies) which used above those concept hierarchies are created in the context of animals categories, namely According to family $CH_a$ (ImageNet), According to diet $CH_b$, and According to region of living $CH_c$. This solution can resolve the three issues: Choosing the best generalization for a set of concepts, discovering the relationship between concepts, and discovering hidden concepts. In the next section we will present the details of the proposed solution in this thesis.

## VII.3. Applying Semantic Similarity in our study

As it has been mentioned, there are many methods that compute the SS between pairs of concepts but none of them consider the case of multiple concepts, which raises a serious problem. Because the query may contain more than two concepts, the SS between of these concepts need to be calculated simultaneously. To do so, we propose a generalization of the aforementioned methods so the SS can be calculated among multiple concepts $C_1$, $C_2$, …$C_n$. an SS among the given concepts is computed using each CH

(Figure VII.3). Thereafter, we select the max SS that corresponds to the appropriate CH this solve the first issue, and the best fit level to discover the relationships between the concepts this solve the second issue, and then based on the relationship selected we can infer the rest of hidden concepts under this relationship this solve the third issue. The steps of the second solution proposed shown in Figure VII.2.

Our approach can be resumed in the following steps:

1. The user submits a set of images, each of which is annotated with one concept those concepts representing the query Q = {C1, C2, C3…Cn}. Then, we compute the semantic similarity SS in each CH. We use equation of Lin (Lin, 1998) to find the similarity between each pair of concepts:

$$sim_L(c_i, c_j) = 2 \times \log(p(lso(c_i, c_j))) / \log(p(c_i)) + \log(p(c_j)) \qquad (20)$$

2. We compute the average similarity Avr-Sim of all concepts in each CH. The average similarity is defined as following:

$$\text{Avr-Sim}(C_1, C_2, \ldots C_n) = \frac{1}{[n(n-1)]/2} \sum_{\substack{i,j=1 \\ i \neq j}}^{n} \text{Sim}_L(\text{Ci,Cj}) \qquad (21)$$

3. We compute the Avr-sim in all types of concept hierarchies, we have three indexes (CHa: by family, CHb: by diet, CHc: by region of living),which means we have three Avr-sim (Avr-sim$_a$ , Avr-sim$_b$ ,Avr-sim$_c$ ). Finely , we select the index that has the Max Avr-sim:

$$CH^* = \text{Maxargm}\left(\text{Avr-simA, Avr-simB,Avr-simC}\right) \qquad (22)$$

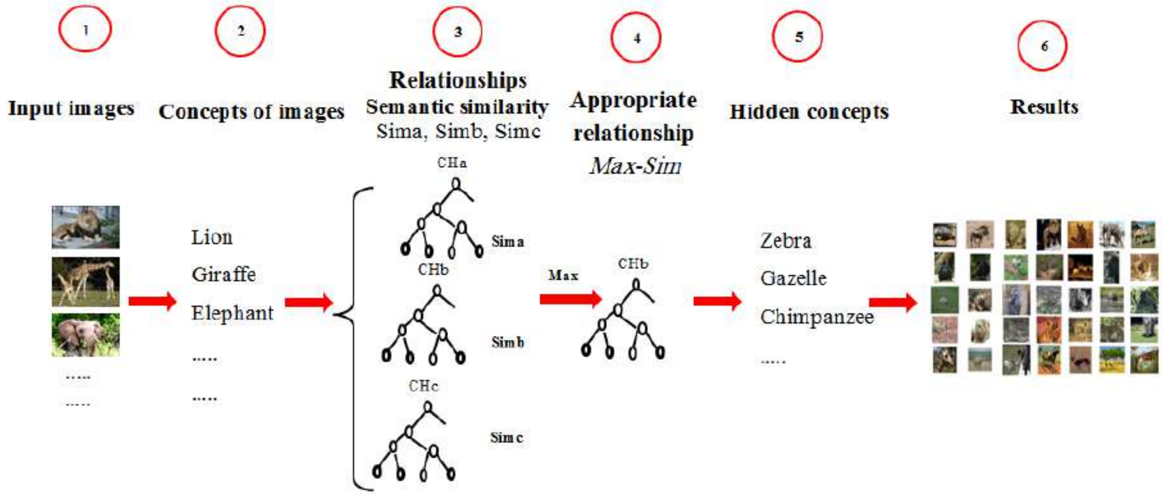



**Figure VII.2. Illustration of the steps of the second solution proposed.**

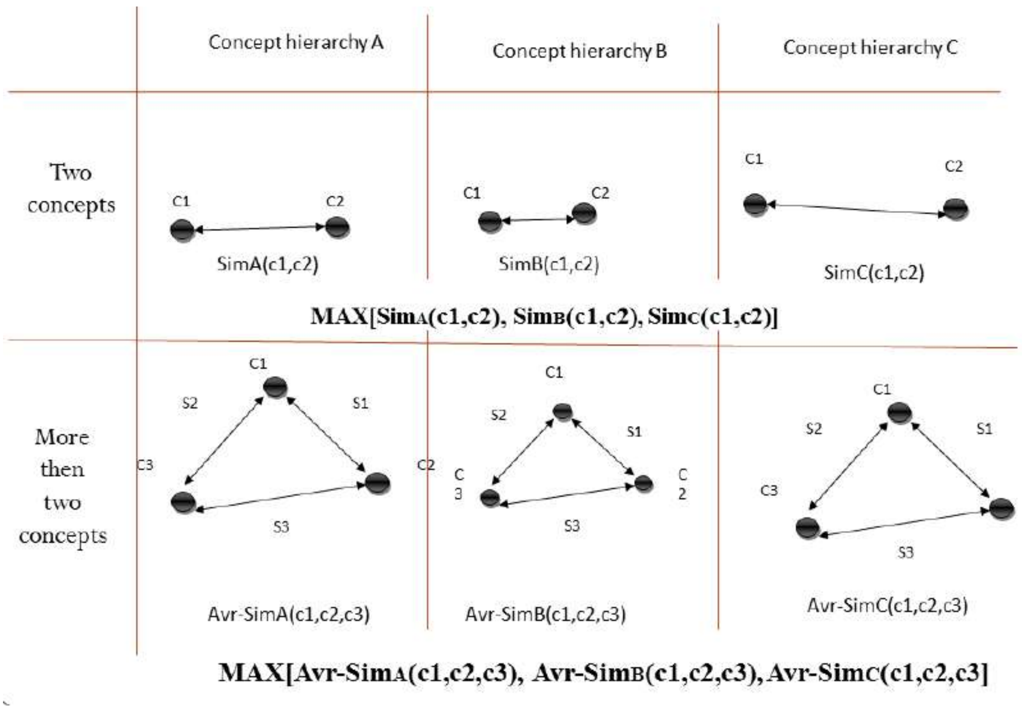



**Figure VII.3.Illustration of the select concept hierarchy CH. Out algorithm use CH which have the Max of SS to analyzing the queries for select the appropriate relationship.**

## VII.4. Eliminate noisy concepts in the query

In the step of query formulation, users may unintentionally make mistakes by choosing irrelevant images (an example given in Figure VII.4). This leads to the misunderstanding between the user and the image engine. To overcome this drawback, an outlier detection technique has been employed to find and eliminate noisy concepts in the query. We compute the distance between each concept and the other concepts. We use the distance proposed by Jiang-Conrath (Jiang & Conrath, 1997). The distance (*Dist*) between each concept and the other concepts is given as following:

$$Dist\ C_i = \sum_{\substack{j=n \\ j \neq i}}^{j=1} Dis(\,C_i, C_j) \qquad (23)$$

Where n is the number of concepts in the query.

A concept is declared as noisy if it holds a distance that exceeds a certain threshold. This allows us to eliminate noisy and achieve better understanding of user intention.

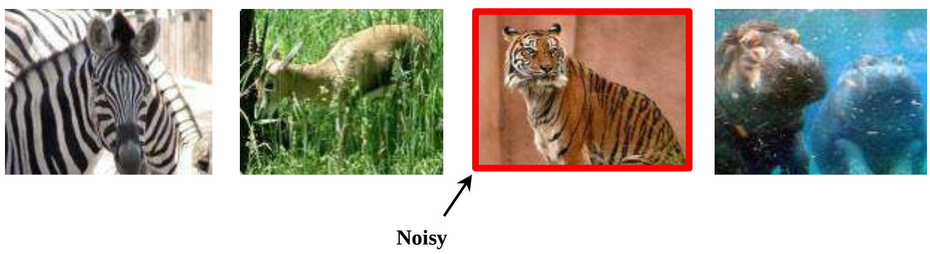



**Figure VII.4. Query contain noisy. Our algorithm eliminate this noisy to improve the performance.**

The steps of analyzing query are summarized in Algorithm 2.

**Algorithm 2:** Generalization of query using SS

```
Begin
    INPUT: Q = {C1, C2, …Cn}
    if  n=2 then
        Compute Sim_A(c1,c2), Sim_B(c1,c2), Sim_C(c1,c2)
        Max (Sim_A(c1,c2), Sim_B(c1,c2), Sim_C(c1,c2))
        Select  CH*  and L*
        Find Hidden C_i
    end if
    if  n>2 then
        Compute Sim_A(ci,cj) , Sim_B(ci,cj), Sim_C(ci,cj)
        Finding the noise C* if existed.
        Remove C*
        Compute Avr-Sim_A(C1, C2, C3…Cn), Avr-Sim_B(C1, C2, C3…Cn), Avr-
        Sim_C(C1, C2, C3…Cn).
    end if
    Max (Avr-sim_A ,Avr-sim_B , Avr-sim_C )
    Select  CH* and L*
    Find Hidden C_i
    OUTPUT: Result of images I_i.
End
```

## VII.5. Analyzing the query in our approach using SS

To explain the idea of analyzing the query, we take as example the two concepts *Lion* and *Tiger*. The SS between *Lion* and *Tiger* is different according to the concept hierarchy. Accurately, the relationship between *Lion* and *Tiger* is *Big cat* in CHa, SimA (Lion, Tigre) =1.86. However, in CHb they have no relationship between them SimB (Lion, Tigre) =0, and in the CHc they have a relationship that is less strong then the one of CHa, SimC (Lion, Tigre) =0.43. Our system favors the strange relationship that allows us to coming closer to human performance.

We can summarize our analyzing of the query in four basic steps:

**1- Refinement of the query:**

In this first step, we analyze the concepts chosen by the user to determine what exactly he is looking for. The result of this step is a set of concepts that may belong to different levels of abstraction in different CHs.

**2-Compute the SS** between **concepts:**

This step use different CH to find the relationship between concepts. Furthermore, the result of this step is the relationship between the concepts of the query.

**3-Checking the existence of the noisy concept**

Using similarity between concepts allow us to find the noisy concept in the query. In order to determine the concept noisy we compute the SS between each pair of concepts and then we compute the average similarity of each concept compared to other concepts. The noisy concept is the concept witch has the smallest value of similarity compared with others concepts. If the concepts are all closer to each other, here we can say that there is no noisy concept.

**4- Discover the hidden concepts**

This step uses the selected relationship in the second step to find the hidden concepts which have a relationship with the concepts of the query. Finally our algorithm returns the relevant images (the images which are annotated with the concepts query and hidden concepts) to the user.

In the analyzing the query in our approach we have two case, case where the query contain two concepts and case where the query contain more than two concepts.

### VII.5.1. Case where the query contain two concepts

When a query contains two concepts, we calculate the similarity in each Hierarchical grouping and select the relationship which has the max similarity. For instance, Query 1 contains 2 images (see Figure VII.5) which mean 2 concepts; Image 1 labeled with the concept "Wolf" and Image 2 labeled with the concept "Fox". The Concepts Query is X= {Wolf, Fox} with n=2 (Number of the positive examples).

*Image 1*

*Image 2*

**Figure VII.5. Illustration of the Query 1 contain 2 concepts.**

The next step is to calculate the SS between these concepts in each CH using the equations presented in Table 7.

**Table 7 . Analyzing of Query 1 using SS**

| Concept hierarchy | Lowest Super Ordinate | Semantic similarity |
|---|---|---|
| **CHa** | **Canine** | **SimA**(Wolf, Fox)=2× log( p(Canine )/ [p(Wolf)+p( Fox)]=0.8 |
| **CHb** | **Carnivores** | **Sim***B*(Wolf, Fox)=2× log( p(Carnivores)/ [p(Wolf)+p(Fox)]=0.6 |
| **CHc** | **North America** | **SimC**(Wolf, Fox)=2× log( p(North America)/ [p(Wolf)+p(Fox)]=0.4 |

Through the results given by Table 7, the maximum Sim of the Query 1 is: Max***Sim*** (Wolf, Fox)=**SimA**(Wolf, Fox), which means the the relationship is: "Canine".

Hidden concepts are the concepts that situated under the concepts of "**Canine**" such as Wild dog, Hyena,… etc.

Figure **VII**.6 presents the results of Query 1 that contain all the images annotated with concepts of "**Canine**".


**Figure VII.6. Results Illustration of the Query 1.**

For instance, Query 2 contains 2 images (see Figure VII.7) which mean 2 concepts; Image 1 labeled with the concept "Bear" and Image 2 labeled with the concept "Chimpanzee". The Concepts Query is X= {Bear, Chimpanzee}.

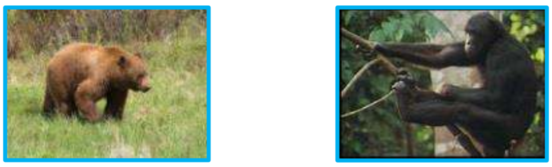


*Image 1* *Image 2*

**Figure VII.7. Illustration of the Query 2 contain 2 concepts.**

The next step is to calculate the SS between these concepts in each CH using the equations presented in Table 8.

**Table 8. Analyzing of Query 2 using SS**

| Concept hierarchy | Lowest Super Ordinate | Semantic similarity |
|---|---|---|
| **CHa** | **Mammal** | **SimA**(Bear ,Chimpanzee )=2× log( p(Mammal)/ [p( Bear )+p( Chimpanzee )]=0.4 |
| **CHb** | **Omnivores** | **Sim***B*(Bear ,Chimpanzee )=2× log( p(Omnivores)/ [p( Bear )+p( Chimpanzee )]=0.9 |
| **CHc** | **/** | **SimC**(Bear, Chimpanzee ) =0 |

Through the results given by Table 8, the maximum Sim of the Query 2 is: Max-***Sim***(Bear, Chimpanzee)=**SimB**(Bear, Chimpanzee), which means the relationship : "Omnivores".

Hidden concepts are the concepts that situated under the concepts of "Omnivores" such as Spider monkey, Skunk, Asiatic black Bear,… etc.

Figure VII.8 presents the results of Query 2 that contain all the images annotated with concepts of "Omnivores".


**Figure VII.8. Results Illustration of the Query 2.**

## VII.5.2. Case where the query contain more than two concepts

Query 3 contains 3 images (see Figure VII.9) which means 3 concepts; Image 1 labeled with the concept "Tiger", Image 2 labeled with the concept "Lion", Image 3 labeled with the concept "Cougar". The Concepts Query is X= { Tiger, Lion, Cougar }.

Image 1 Image 2 Image 3

**Figure VII.9. Illustration of the Query 3.**

The next step is to calculate the SS among these concepts in each CH using the equations presented in Table 9.

**Table 9. Analyzing of Query 3 using SS**

| Concept hierarchy | Lowest Super Ordinate | Avr-Semantic similarity |
|---|---|---|
| **CHa** | Big cat | ***Avr-Sim***A(Tiger, Lion, Cougar)=0.9 |
| **CHb** | Carnivores | ***Avr-SimB***(Tiger, Lion, Cougar)=0.6 |
| **CHc** | / | ***Avr-Sim***C(Tiger, Lion, Cougar)=0 |

From the results in the Table 9, the Maximum Avr-Sim of the Query 3 is:

**MAX** ***Avr-Sim=Avr-Sim***A(Tiger, Lion, Cougar) which means that the relationship is: "Big cat". The Hidden concepts are: The rest of the "Big cat" animals (Leopard, Panther, Ocelot, Cougar, Coyote).

Figure VII.10 shows the results of Query 3 that contain all the images annotated with concepts of "Big cat".

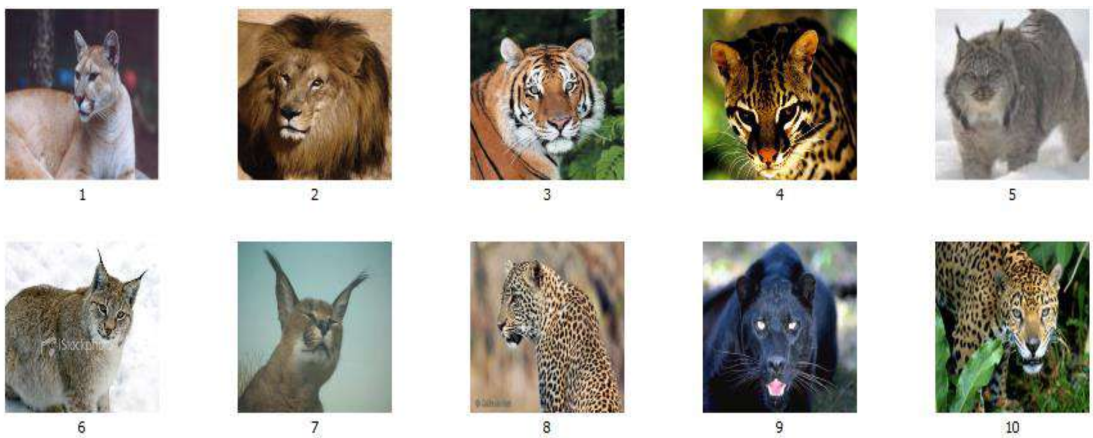



**Figure VII.10. Results Illustration of the Query 3.**

Query 4 contains 3 images (see Figure VII.11) which means 3 concepts; Image 1 labeled with the concept "Tiger", Image 2 labeled with the concept "Panda", Image 3 labeled with the concept "Bear". The Concepts Query is X= {Tiger, Panda, Bear}.

Image 1 Image 2 Image 3

**Figure VII.11. Illustration of the Query 4.**

The next step is to calculate the SS among these concepts in each CH using the equations presented in Table 10.

**Table 10. Analyzing of Query 4 using SS**

| Concept hierarchy | Lowest Super Ordinate | Avr-Semantic similarity |
|---|---|---|
| **CHa** | Mammal | ***Avr-Sim***A(Tiger, Panda, Bear)=0.3 |
| **CHb** | / | ***Avr-SimB***(Tiger, Panda , Bear )=0 |
| **CHc** | Asia animals | ***Avr-Sim***C(Tiger, Panda , Bear )=0.9 |

From the results in the Table 10, the Maximum Avr-Sim of the Query 4 is:

**MAX *Avr-Sim=Avr-Sim***C(Tiger, Lion, Cougar) which means that the relationship is: "Asia animals".

The Hidden concepts are: The rest of the "Asia animals" animals (Indian Elephant, Panther, Raccoon Dog, Malaya Tapir, Rock hopper..).

Figure VII.12 shows the results of query 4 that contain all the images annotated with concepts of “Asia animals”.

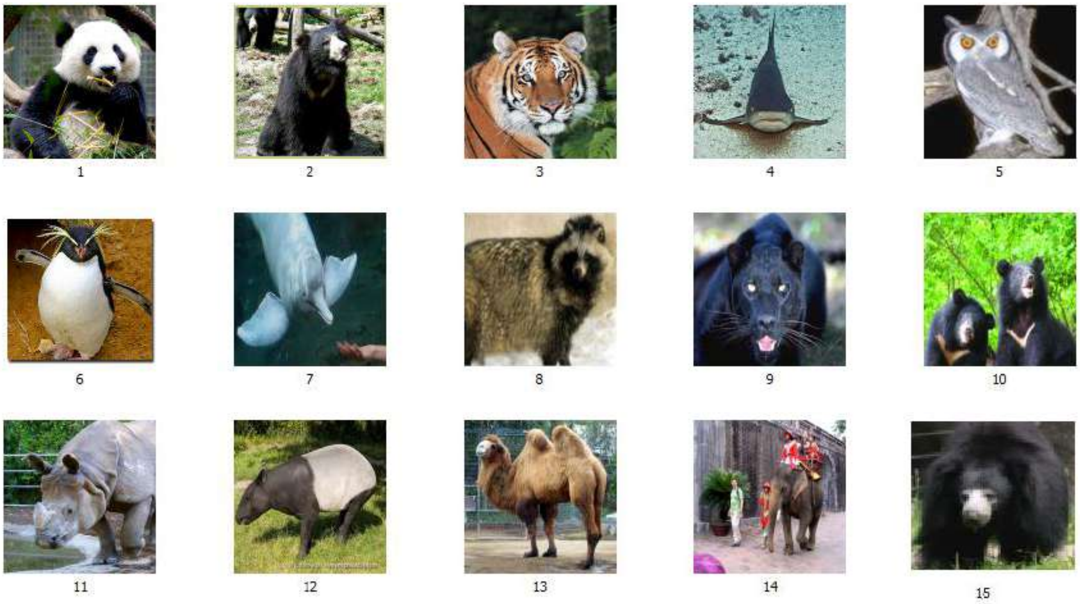



**Figure VII.12. Results Illustration of the Query 4.**

From these results, we can see that our algorithm is capable of analyzing the query in multiple concept hierarchies by solving the three issues: Finding the appropriate relationship among concepts regardless the kind of the relationship, Choosing the best generalization for a set of concepts, Finding the hidden concepts to enrich the results and expand the query. In addition, our algorithm is able to indicate and eliminate noisy concepts, which proves the effectiveness and efficiency of our algorithm in user intention understanding.

## VII.6. Conclusion

In this chapter, we have presented the details of the second solution proposed in this thesis which solve the three issues of our search. This solution focuses on the analysis of the concepts query by using a new metric of semantic similarity. We have used the semantic similarity between a set of concepts based in multiple concept hierarchies used in the first solution. Firstly, to find the relationships between concepts we have computed the semantic similarity in each concept hierarchy, and then we discovered the appropriate relationships by selecting the max-Sim between all SS in the three hierarchies. Finally, we have extracted all hidden concepts in order to expand the query, and give all the needs of user in the context of image retrieval. Further, we have demonstrated the effectiveness of the algorithm by giving examples of queries with the details of the analyzing and the results obtained.

# CONCLUSION AND FUTURE WORK

In this thesis, we have focused on three general issues in the specific context of semantic concepts-based image retrieval: discovering the relationships between concepts, discovering the appropriate generalization and finally discovering the hidden concepts for the expansion of the query.

In order to sole the three issues presented above, we have proposed tow novel solutions, each of which takes simultaneously into account the three issues. In both solutions, we use ImageNet database which indexed according to the hierarchy of Word Net. In addition, our concepts in the dataset are represented using a multiple concept hierarchies (ontologies) instead one concept hierarchy, that allowing to perform the best generalization.

- **The first solution** is based on **Bayesian Model of Generalization (BMG)** model, the contributions of this solution were as follows:
    - **Discovering all relationships** based on the concepts observed in the query. We created the hypotheses space witch are the relationships between concepts that are in the three concept hierarchies. This step solved the second issue (Discovering the relationships between concepts).

- **Finding the best generalization**. We calculating the posterior probability for each hypothesis, we take the max a posterior hypothesis $h_{MAP}$ as the appropriate relationship. Hence we choose the best generalization. This step solved the first issue (Discovering the best generalization).

- **Finding hidden concepts,** when the best generalization selected and the relationships discovered, we discover the other concepts under the relationship selected to enrich the query with, in the context of query expansion attempt.

Here, the process of generalization ends. The results contain all annotated images with concepts that fall within the context of the appropriate relationship.

- **The second solution** is based on measuring the **Semantic similarity (SS)** between a set of concepts. Instead of pairwise metrics, we have proposed a new similarity metric that allows to calculate the semantic similarity between several concepts (more than two concepts)

  The contributions of the second solution were as follows:

  - **To find relationships** between the concepts of the query, we calculate the semantic similarity or average semantic similarity between concepts in each concept hierarchy. That is, we have identified relations. Thus, the second problem solved the relationship between concepts.

  - **Finding the appropriate relationship or the best generalization:** The relationship that contains the maximum semantic similarity between concepts is the appropriate relationship. By finding this relationship, we have achieved best generalization.

  - **Finding hidden concepts**: Based on the appropriate relationship selected in the previous step we extract hidden concepts which are the brothers of the concepts query in the hierarchy.

Here, the process of generalization ends, so the results contain all the annotated images with the concepts that under the appropriate relationship. In addition, our second solution allows also to **detect the noisy concept in the query** (outliers) and therefore to discard them, which could help improving retrieval precision.

We have used the both solutions in the context of the image retrieval semantic concepts-based image retrieval which yields to add several contributions in the image retrieval:

- Developed a new image retrieval engine that exploits the query expansion method explained above.
- Resolved the challenging task of grasping user intention and understanding his needs.
- The retrieval engine becomes able to answer the user needs adequately, thereby alleviating the intention gap and the semantic gap.
- Introduced two new concept hierarchies according to new grouping principles: diet and place of living. Those hierarchies are used for our experimental validation.

We have used the precision and recall to present the effectiveness of the proposed method. The results demonstrate that our two proposed approach is capable to discovering the appropriate relationship between concepts, and determining the appropriate concepts hierarchy, and finally discover the hidden concepts.

The obtained results show the strength and the effectiveness of the proposed approach, the proposed approach has also proven its strength against the conventional approach.

As an active research area, there are many new research ideas to develop the generalization of the concepts in the context of image retrieval. We consider extending the concept hierarchies by adding new other type of concept hierarchy (Use more than three concept hierarchies) in order to surround user's thinking to better understand his intentions.

In addition, we will consider applying the proposed solutions to fields others than image retrieval such as Machine learning, Artificial intelligence. In fact it can be applied to different situations where generalization selection and concept discovery is needed.

# BIBLIOGRAPHY

Abbott, J., Austerweil, J., & Griffiths, T. (2012). *Constructing a hypothesis space from the Web for large-scale Bayesian word learning.* Paper presented at the Proceedings of the Cognitive Science Society.

Aiadi, O. (2017). *Combler le fossé sémantique en recherche d'image via la transformation des concepts sémantique en une représentation visuelle.* (PhD thesis), Univ. Kasdi Merbah Ouargla.

Aiadi, O., & Kherfi, M. L. (2017). A new method for automatic date fruit classification. *International Journal of Computational Vision and Robotics, 7*(6), 692-711.

Ambika, P., & Samath, J. A. (2012). *Ontology—Based semantic web CBIR by utilizing content and model annotations.* Paper presented at the International Conference on Pattern Recognition, Informatics and Medical Engineering (PRIME-2012).

Ashley, J. J., Barber, R., Flickner, M. D., Hafner, J. L., Lee, D., Niblack, C. W., & Petkovic, D. (1995). *Automatic and semiautomatic methods for image annotation and retrieval in query by image content (QBIC).* Paper presented at the Storage and retrieval for image and video databases III.

Bakar, S. A., Hitam, M. S., & Yussof, W. N. J. H. W. (2013). *Content-based image retrieval using SIFT for binary and greyscale images.* Paper presented at the 2013 IEEE International Conference on Signal and Image Processing Applications.

Borst, W. N., & Borst, W. (1997). Construction of engineering ontologies for knowledge sharing and reuse.

Carey, S. (1978). *The child as word learner*: na.

Chen, L., Xu, D., Tsang, I. W., & Luo, J. (2010). *Tag-based web photo retrieval improved by batch mode re-tagging.* Paper presented at the Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on.

Clough, P., & Sanderson, M. (2006). User experiments with the Eurovision cross-language image retrieval system. *Journal of the American Society for Information Science and Technology, 57*(5), 697-708.

Datta, D., Varma, S., & Singh, S. K. (2017). Multimodal retrieval using mutual information based textual query reformulation. *Expert Systems with Applications, 68*, 81-92.

Debbagh, F., Kherfi, M. L., & Babahenini, M. C. (2017). A semantic relatedness-based solution for reducing missing problem in TBIR. *International Journal of Signal and Imaging Systems Engineering, 10*(3), 146-156.

Deepa, C. (2017). SABC-SBC: a hybrid ontology based image and webpage retrieval for datasets. *Automatic Control and Computer Sciences, 51*(2), 108-113.

Deng, J., Berg, A. C., & Fei-Fei, L. (2011). *Hierarchical semantic indexing for large scale image retrieval.* Paper presented at the Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on.

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., & Fei-Fei, L. (2009). *Imagenet: A large-scale hierarchical image database.* Paper presented at the Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on.

Deng, J., Krause, J., Berg, A. C., & Fei-Fei, L. (2012). *Hedging your bets: Optimizing accuracy-specificity trade-offs in large scale visual recognition.* Paper presented at the Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on.

Deselaers, T., Keysers, D., & Ney, H. (2004). *FIRE–flexible image retrieval engine: ImageCLEF 2004 evaluation.* Paper presented at the Workshop of the Cross-Language Evaluation Forum for European Languages.

Dinakaran, B., Annapurna, J., & Kumar, C. A. (2010). Interactive image retrieval using text and image content. *Cybern Inf Tech, 10*, 20-30.

Faloutsos, C., Barber, R., Flickner, M., Hafner, J., Niblack, W., Petkovic, D., & Equitz, W. (1994). Efficient and effective querying by image content. *Journal of intelligent information systems, 3*(3-4), 231-262.

Fei-Fei, L., & Perona, P. (2005). *A bayesian hierarchical model for learning natural scene categories.* Paper presented at the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05).

Fellbaum, C. (1998). WordNet. An electronic lexical database. Massachusetts: Cambridge: MIT Press.

Fensel, D., Van Harmelen, F., Horrocks, I., McGuinness, D. L., & Patel-Schneider, P. F. (2001). OIL: An ontology infrastructure for the semantic web. *IEEE intelligent systems, 16*(2), 38-45.

Filali, J., Zghal, H., & Martinet, J. (2016). *Towards visual vocabulary and ontology-based image retrieval system.* Paper presented at the International Conference on Agents and Artificial Intelligence.

Gerken, L. (2004). Nine-month-olds extract structural principles required for natural language. *Cognition, 93*(3), B89-B96.

Gerken, L. (2006). Decisions, decisions: Infant language learning when multiple generalizations are possible. *Cognition, 98*(3), B67-B74.

Glick, J., & Miller, K. (2016). Insect Classification With Heirarchical Deep Convolutional Neural Networks.

Gómez-Pérez, A. (1999). Ontological engineering: A state of the art. *Expert Update: Knowledge Based Systems and Applied Artificial Intelligence, 2*(3), 33-43.

Gruber, T. R. (1993). A translation approach to portable ontology specifications. *Knowledge acquisition, 5*(2), 199-220.

Jia, Y., Abbott, J. T., Austerweil, J. L., Griffiths, T., & Darrell, T. (2013). *Visual concept learning: Combining machine vision and bayesian generalization on concept hierarchies.* Paper presented at the Advances in Neural Information Processing Systems.

Jiang, J. J., & Conrath, D. W. (1997). Semantic similarity based on corpus statistics and lexical taxonomy. *arXiv preprint cmp-lg/9709008*.

Josephson, J. R. (2000). Smart inductive generalizations are abductions *Abduction and induction* (pp. 31-44): Springer.

Karthikeyan, K., & Karthikeyani, V. (2015). Ontology based concept hierarchy extraction of web data. *Indian Journal of Science and Technology, 8*(6), 536.

Khaldi, B. (2017). *De Nouvelles Caractéristiques pour la Recherche d'Images.* (PhD thesis), Univ. Kasdi Merbah Ouargla.

Khaldi, B., & Kherfi, M. L. (2016). Modified integrative color intensity co-occurrence matrix for texture image representation. *Journal of Electronic Imaging, 25*(5), 053007-053007.

Kherfi, M. L. (2008). Review of human-computer interaction issues in image retrieval *Advances in Human Computer Interaction*: IntechOpen.

Kherfi, M. L., Ziou, D., & Bernardi, A. (2002). *Learning from negative example in relevance feedback for content-based image retrieval.* Paper presented at the Pattern Recognition, 2002. Proceedings. 16th International Conference on.

Kherfi, M. L., Ziou, D., & Bernardi, A. (2003). Combining positive and negative examples in relevance feedback for content-based image retrieval. *Journal of Visual Communication and Image Representation, 14*(4), 428-457.

Korichi, M., Kherfi, M. L., Batouche, M., & Bouanane, K. (2018). Extended Bayesian generalization model for understanding user's intention in semantics based images retrieval. *Multimedia Tools and Applications, 77*(23), 31115-31138.

Lassila, O., & Swick, R. R. (1999). Resource description framework (RDF) model and syntax specification.

Leacock, C., & Chodorow, M. (1998). Combining local context and WordNet similarity for word sense identification. *WordNet: An electronic lexical database, 49*(2), 265-283.

Leutenegger, S., Chli, M., & Siegwart, R. (2011). *BRISK: Binary robust invariant scalable keypoints.* Paper presented at the 2011 IEEE international conference on computer vision (ICCV).

Lew, M. S., Sebe, N., Djeraba, C., & Jain, R. (2006). Content-based multimedia information retrieval: State of the art and challenges. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 2*(1), 1-19.

Lin, D. (1998). *An information-theoretic definition of similarity.* Paper presented at the Icml.

Liu, H. (2012). *Research of image retrieval system framework based on ontology and content.* Paper presented at the Fourth International Conference on Machine Vision (ICMV 2011): Machine Vision, Image Processing, and Pattern Analysis.

Liu, Y.-N., Zhang, S.-S., Sang, Y., & Wang, S.-M. (2019). Improving image retrieval by integrating shape and texture features. *Multimedia Tools and Applications, 78*(2), 2525-2550.

Liu, Y., Xu, D., Tsang, I. W., & Luo, J. (2011). Textual query of personal photos facilitated by large-scale web data. *IEEE transactions on pattern analysis and machine intelligence, 33*(5), 1022-1036.

Liu, Y., Zhang, D., Lu, G., & Ma, W.-Y. (2004). *Region-based image retrieval with perceptual colors.* Paper presented at the Pacific-Rim Conference on Multimedia.

Lowe, D. G. (1999). *Object recognition from local scale-invariant features.* Paper presented at the Computer vision, 1999. The proceedings of the seventh IEEE international conference on.

Ma, W.-Y., & Manjunath, B. S. (1999). Netra: A toolbox for navigating large image databases. *Multimedia systems, 7*(3), 184-198.

Manjunath, B. S., Ohm, J.-R., Vasudevan, V. V., & Yamada, A. (2001). Color and texture descriptors. *IEEE Transactions on circuits and systems for video technology, 11*(6), 703-715.

McBride, B. (2004). The resource description framework (RDF) and its vocabulary description language RDFS *Handbook on ontologies* (pp. 51-65): Springer.

Medina, L. A., Fred, A. L., Rodrigues, R., & Filipe, J. (2012). *Measuring Entity Semantic Relatedness using Wikipedia.* Paper presented at the KDIR.

Mihalcea, R., Corley, C., & Strapparava, C. (2006). *Corpus-based and knowledge-based measures of text semantic similarity.* Paper presented at the AAAI.

Mojsilovic, A., Gomes, J., & Rogowitz, B. E. (2002). *Isee: Perceptual features for image library navigation.* Paper presented at the Human Vision and Electronic Imaging VII.

Natsev, A. P., Haubold, A., Tešić, J., Xie, L., & Yan, R. (2007). *Semantic concept-based query expansion and re-ranking for multimedia retrieval.* Paper presented at the Proceedings of the 15th ACM international conference on Multimedia.

Niblack, C. W., Barber, R., Equitz, W., Flickner, M. D., Glasman, E. H., Petkovic, D., . . . Taubin, G. (1993). *QBIC project: querying images by content, using color, texture, and shape.* Paper presented at the Storage and retrieval for image and video databases.

Noy, N. F., & McGuinness, D. L. (2001). Ontology development 101: A guide to creating your first ontology: Stanford knowledge systems laboratory technical report KSL-01-05 and ….

Park, G., Baek, Y., & Lee, H.-K. (2003). *Majority based ranking approach in web image retrieval.* Paper presented at the International Conference on Image and Video Retrieval.

Plataniotis, K. N., & Venetsanopoulos, A. N. (2000). *Color image processing and applications*: Springer.

Popescu, A., Moëllic, P.-A., & Millet, C. (2007). *Semretriev: an ontology driven image retrieval system.* Paper presented at the Proceedings of the 6th ACM international conference on Image and video retrieval.

Qi, Y., Song, Y.-Z., Zhang, H., & Liu, J. (2016). *Sketch-based image retrieval via siamese convolutional neural network.* Paper presented at the 2016 IEEE International Conference on Image Processing (ICIP).

Quattoni, A., Collins, M., & Darrell, T. (2008). *Transfer learning for image classification with sparse prototype representations.* Paper presented at the Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on.

Rada, R., Mili, H., Bicknell, E., & Blettner, M. (1989). Development and application of a metric on semantic nets. *IEEE Transactions on Systems, man, and cybernetics, 19*(1), 17-30.

Rasiwasia, N., Moreno, P. J., & Vasconcelos, N. (2007). Bridging the gap: Query by semantic example. *IEEE Transactions on Multimedia, 9*(5), 923-938.

Rasiwasia, N., & Vasconcelos, N. (2008). *A study of query by semantic example.* Paper presented at the 2008 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops.

Resnik, P. (1995). Using information content to evaluate semantic similarity in a taxonomy. *arXiv preprint cmp-lg/9511007*.

Saffran, J. R., & Wilson, D. P. (2003). From syllables to syntax: multilevel statistical learning by 12-month-old infants. *Infancy, 4*(2), 273-284.

Salakhutdinov, R., Torralba, A., & Tenenbaum, J. (2011). *Learning to share visual appearance for multiclass object detection.* Paper presented at the Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on.

Shepard, R. N. (1987). Toward a universal law of generalization for psychological science. *Science, 237*(4820), 1317-1323.

Stevens, R., Goble, C. A., & Bechhofer, S. (2000). Ontology-based knowledge representation for bioinformatics. *Briefings in bioinformatics, 1*(4), 398-414.

Styrman, A. (2005). *Ontology-based image annotation and retrieval.* Master thesis.

Swingley, D. (2005). Statistical clustering and the contents of the infant vocabulary. *Cognitive psychology, 50*(1), 86-132.

Taieb, M. A. H., Aouicha, M. B., & Hamadou, A. B. (2014). Ontology-based approach for measuring semantic similarity. *Engineering Applications of Artificial Intelligence, 36*, 238-261.

Tenenbaum, J. B. (1999). *Bayesian modeling of human concept learning.* Paper presented at the Advances in neural information processing systems.

Tenenbaum, J. B. (2000). *Rules and similarity in concept learning.* Paper presented at the Advances in neural information processing systems.

Tenenbaum, J. B. (2007). Word learning as Bayesian inference. *Psychological review, 114*(2), 245.

Tenenbaum, J. B., & Griffiths, T. L. (2001). Generalization, similarity, and Bayesian inference. *Behavioral and brain sciences, 24*(4), 629-640.

Tolias, G., & Jégou, H. (2014). Visual query expansion with or without geometry: refining local descriptors by feature aggregation. *Pattern recognition, 47*(10), 3466-3476.

Verma, N., Mahajan, D., Sellamanickam, S., & Nair, V. (2012). *Learning hierarchical similarity metrics.* Paper presented at the Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on.

Wang, J., Li, J., Chan, D., & Wiederhold, G. (1999). Semantics-sensitive retrieval for digital picture libraries. *D-Lib Magazine, 5*(11).

Wang, J. Z., Li, J., & Wiederhold, G. (2001). SIMPLIcity: Semantics-sensitive integrated matching for picture libraries. *IEEE Transactions on Pattern Analysis & Machine Intelligence*(9), 947-963.

Wu, L., Hoi, S. C., Jin, R., Zhu, J., & Yu, N. (2009). *Distance metric learning from uncertain side information with application to automated photo tagging.* Paper presented at the Proceedings of the 17th ACM international conference on Multimedia.

Wu, Z., & Palmer, M. (1994). *Verbs semantics and lexical selection.* Paper presented at the Proceedings of the 32nd annual meeting on Association for Computational Linguistics.

Xu, F., & Tenenbaum, J. B. (2007). Word learning as Bayesian inference. *Psychological review, 114*(2), 245.

Yan, Z., Zhang, H., Piramuthu, R., Jagadeesh, V., DeCoste, D., Di, W., & Yu, Y. (2015). *HD-CNN: hierarchical deep convolutional neural networks for large scale visual recognition.* Paper presented at the Proceedings of the IEEE International Conference on Computer Vision.

Yang, H. (2011). *Personalized concept hierarchy construction.* University of Southern California.

Yang, L., Jin, R., Mummert, L., Sukthankar, R., Goode, A., Zheng, B., . . . Satyanarayanan, M. (2010). A boosting framework for visuality-preserving distance metric learning and its application to medical image retrieval. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 32*(1), 30-44.

Zha, Z.-J., Yang, L., Mei, T., Wang, M., & Wang, Z. (2009). *Visual query suggestion.* Paper presented at the Proceedings of the 17th ACM international conference on Multimedia.

Zhang, D., & Lu, G. (2002). Shape-based image retrieval using generic Fourier descriptor. *Signal Processing: Image Communication, 17*(10), 825-848.

Zhang, S.-B., & Lai, J.-H. (2015). Semantic similarity measurement between gene ontology terms based on exclusively inherited shared information. *Gene, 558*(1), 108-117.